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Regional Recreation Demand Models for Large Reservoirs: Database Development, Model Estimation, and Management Applications

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Prepared for Headquarters, U.S. Army Corps of Engineers

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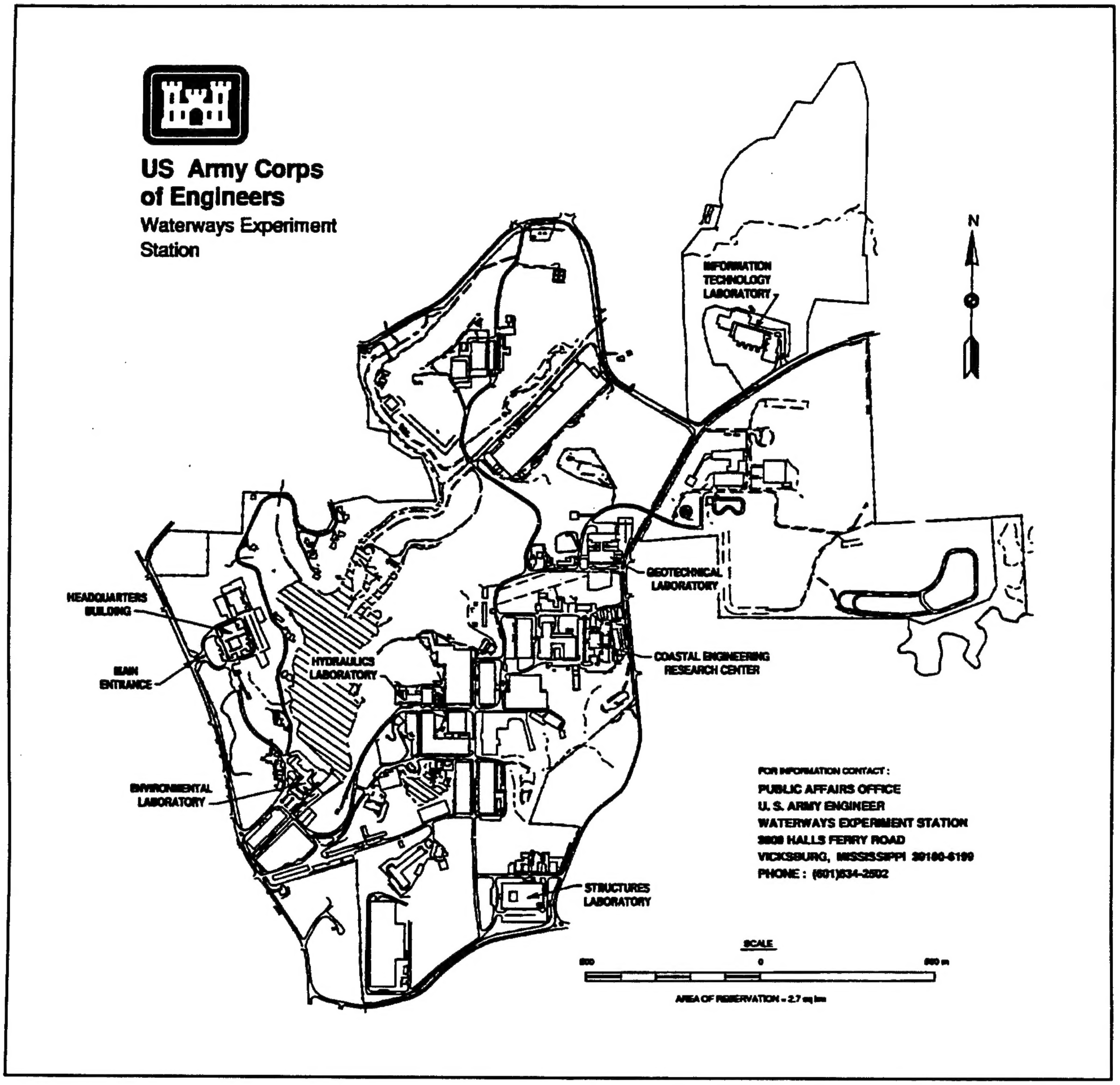

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Preface

The work reported herein was conducted as part of the Natural Resources Research Program (NRRP) under the Regional Recreation Demand Model (RRDM), Work Unit 32574, Mr. Jim E. Henderson, Principal Investigator. The NRRP is sponsored by Headquarters, U.S. Army Corps of Engineers (HQUSACE), and is assigned to the U.S. Army Engineer Waterways Experiment Station (WES) under the purview of the Environmental Laboratory (EL). Funding was provided under Department of the Army Appropriation No. 96X3121, General Investigation. The NRRP is managed under the Environmental Resources Research and Assistance Programs (ERRAP), Mr. J. L. Decell, Manager. Mr. Russell Tillman was Assistant Manager, ERRAP, for the NRRP. Program monitors during the study were Mr. Robert Daniel and Ms. Judy Rice, HQUSACE.

The report documents the development of RRDM for large reservoirs and applies the developed model to operations and management questions. The development of the RRDM was conducted through an Interagency Agreement with the U.S. Department of Agriculture (USDA) Cooperative State Research Service (CSRS), now known as the Cooperative State Research, Education, and Extension Service. Dr. John Meadows, USDA, managed the agreement for the USDA, CSRS. Development of the RRDM was coordinated by three principal investigators, Dr. Frank A. Ward, New Mexico State University; Dr. John B. Loomis, University of California-Davis (now at Colorado State University); and Dr. Richard C. Ready, University of Kentucky. Mr. Brian A. Roach, University of California-Davis, was responsible for establishing and maintaining the database and for performing much of model estimation process. Mr. Jim E. Henderson, Resource Analysis Branch (RAB), WES, acted as principal investigator for the work unit and provided assistance in the acquisition, use, and interpretation of Corps of Engineers data, advice in development of applications of the RRDM, and continued review of the RRDM development process.

The data used to develop the RRDM were collected by Corps of Engineers Districts at reservoir projects through recreation-use surveys in the mid-1980's. Data from the U.S. Army Engineer Districts, Little Rock, Nashville, and Sacramento, were used to develop the RRDM. For their help, thanks go to Messrs. Joe Holmberg and George Nichols, Sacramento District;

Gary Whisnant, Dale Leggett, and Maragret Rohan, Little Rock District; and Todd Yann, Ton Raines, and Linda Lee, Nashville District.

Mr. William J. Hansen, U.S. Army Corps of Engineers (USACE) Institute for Water Resources, Fort Belvoir, VA, provided advice, review, and consultation throughout the study. Mr. Scott Jackson, WES, provided review for the study and assisted in the interpretation and data manipulations for the recreation use data.

This report was prepared under the general supervision of Mr. H. Roger Hamilton, Chief, RAB; Dr. Robert M. Engler, Chief, Natural Resources Division; and Dr. John W. Keeley, Director, EL.

At the time of publication of this report, Director of WES was Dr. Robert W. Whalin. Commander was COL Bruce K. Howard, EN.

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Summary

This report describes and documents the development and application of a series of regional travel cost models. These models estimate visitation and economic benefits associated with selected management actions carried out at U.S. Army Corps of Engineers (USACE) reservoirs. Objectives are met by assembling a database of recreational visitation, estimating a series of travel cost models, and applying the models to selected management actions.

Regional recreation demand models (RRDM's) are used to estimate the contribution of recreation resources at selected USACE projects to the national economic development benefits associated with different ways of managing water supplies. RRDM's permit managers to transfer estimated visits and benefits to unstudied projects and regions for evaluating the consequences of proposed management actions.

Benefits per recreation visit derived from the estimated travel cost models are used to measure visitor willingness to pay for recreation supplied by USACE. Using regression analysis, visitation rates are found to vary with travel costs per visit, population from counties-of-origin, site facilities, substitute water-based recreation opportunities, and demographic factors. For each county of origin in a project's market area, total recreation benefit is divided by total observed recreation visits to estimate an average per-visit benefit.

Findings indicate average per-visit benefits at USACE reservoirs vary widely according to a reservoir's location, nearness to population centers, availability of substitute recreation, and extent of onsite facilities. For the projects studied here, average benefits per day-use visit in 1994 dollars varied from a high of $6.68 at Lake Isabella in the U.S. Army Engineer District, Sacramento, to a low of $1.87 at both Beaver Lake in the U.S. Army Engineer District, Little Rock, and Lake Mendocino in the Sacramento District. Average benefits per overnight visit ranged from a high of $30.35 at Lake Barkley in the U.S. Army Engineer District, Nashville, to a low of $7.38 at Lake Kaweah in the Sacramento District.

Economic benefits from holding an additional acre foot of water in storage for 1 month are also estimated. These incremental values of water vary according to the amount of existing water in the reservoir, time of year, extent of substitutes, population in the market area, and extent of onsite facilities.

Monthly values produced by an additional acre foot of water range from a high of $52.79 at Lake Millwood in the Little Rock District to a low of $0.27 at Laurel River Lake in the Nashville District. A companion report presents user-friendly software that allows resource planners to estimate the benefits of various recreation resource improvements with the use of interactive PC computer screens (Ward and Martin 1994).

Care, judgment, and wise use of local information should be exercised when attempting to transfer models estimated in one region to reservoir management plans in other regions. Using data on facilities, demographics, substitutes, and travel costs in one region to predict visitation patterns in other regions produces mixed results. Transferring predictions of visitation to a different region from which a model is estimated produces adequate results when conditions at the study and target areas are similar. Transferred visit predictions are poor when conditions are widely dissimilar. However, transfers of average benefits per visit and transfers of incremental values of added facilities are considerably more robust.

1 Introduction

Role of National Economic Welfare in River Basin Management

The planning and operation of U.S. Army Corps of Engineers (USACE) natural resources continues to increase in complexity because of the need to accommodate multiple purposes, many of which compete among each other over time or location. Total economic benefits summed over project purposes is referred to as national economic development (NED) benefits. Total NED benefits as a measure of economic performance guide the formulation, implementation, and evaluation of USACE management plans. These NED benefits depend on storage and release patterns of water and other project improvements implemented at various times and locations.

Economic models are widely used to estimate NED benefits. Several economic and engineering models have been developed by USACE in recent years in an attempt to structure a framework that would permit increasing NED benefits resulting from natural resource management actions. A good example is the network flow linear programming model developed by the Hydrological Engineering Center at Davis California. The model attempts to identify project water management actions that maximize NED benefits. The linear program relies on a model of the hydrology of a river basin and on economic penalty functions that relate total NED benefits to storage and release patterns of water. The model has two basic choice variables that can be varied to achieve an economic optimum: water flows in space and water flows in time (U.S. Army Engineer Hydrologic Engineering Center 1984). To date, this economic optimization model has been applied to the Missouri and Columbia river basins.

Role of Economic Values in Water Allocation Decisions

The economic value of water-based recreation at USACE project facilities is defined as the total willingness to pay for the resource by the recreating public. These values are typically affected by management actions made at

project reservoirs and depend on several factors, including the design size of the project, quantity of water available at that project, time of year, complementary project facilities, demographic factors in the market area (such as the number and characteristics of the people), and substitute recreational opportunities.

However, a lack of market-clearing prices charged to visitors at USACE facilities hinders the measurement of recreational economic values. The lack of reliable data on these recreational values makes it difficult to account for recreational values accurately when attempting to manage systems of USACE projects for maximum NED benefit. It is this lack of reliable data on recreation economic benefits and the federally mandated need to maximize total water-related benefits at USACE projects that motivated the present study.

Need for Information on Impacts of Project Management Decisions on Recreation Visitation and Benefits

Increased demands for limited USACE recreation resources often conflict with changes in operation of USACE projects. To more adequately consider recreation in planning and operations decisions along with navigation and other project purposes, there has been an increased need to improve predictions of changes in recreation demand and use that result from changes in the quantity or quality of recreation resources in a region. One approach to predicting recreation demand is through development of recreation demand models. A regional recreation demand model predicts recreation visitation and benefits under a wide range of management actions, project facilities, population characteristics, and economic conditions that occur at sites throughout a region.

In Fiscal Year 1989, USACE Headquarters initiated the regional recreation demand model work unit under the National Resources Research Program (NRRP). The objective of the work unit was to develop models to predict recreation benefits for USACE Districts to use in support of planning and operations decisionmaking.

Changes in operational plans that alter water levels

One important class of USACE management actions is the changing of reservoir levels. Lake levels at a project can fluctuate because of regional water demands for water supply, navigation, flood storage, hydroelectric, or irrigation. Lake levels also can fluctuate because of changes in operating rules for dams brought about changes in licenses from agencies such as the Federal Energy Regulatory Commission. Droughts or floods also affect lake levels. Lake levels that fluctuate for any of these reasons affect recreation visitation and associated benefits to the resource user. For USACE to

continue operating projects to maximize NED benefits, a model is required that accurately predicts the economic consequences of lake level fluctuations.

Changes in supply of recreation opportunities

The USACE can implement numerous management actions other than varying reservoir levels that affect the supply of recreation opportunities. Adding or renovating parking facilities, implementing day-use fees, and adding picnic or camping facilities are a few examples. Therefore, a model that accurately predicts the consequences of these management actions on visitation and economic benefits at a wide range of projects is a valuable management resource.

Changes in regional demographics

Factors beyond the direct control of project managers affect the demand for recreational use of USACE reservoirs. Several demographic factors that characterize the population in a project's market area should influence recreational visitation. Examples include the distribution of age, ethnicity, income, and various other factors that influence recreational preferences. While USACE cannot influence the evolution of demographic factors directly, project managers can modify facilities to accompany these changes. Economically efficient management decisions would accompany those changes in such a way as to produce the highest possible benefits. For example, income changes in a region are beyond the control of USACE managers. Suppose rising regional income over time increases the demand for boats and reduces the demand for picnic outings. In this circumstance, it is economically efficient for the USACE to invest in more boat launch lanes and less picnic tables. Similar examples can be imagined. In any case, access to a recreation demand and benefits model enables managers to make economically wise decisions in response to changing demographic patterns.

Objectives

The objective of the NRRP work unit is to develop and document regional models that predict recreation use and benefits for USACE districts to use in support of planning and operations decisions. This objective is accomplished by completing three tasks:

a. Assemble a database for a regional recreation demand model.

b. Estimate regional recreation demand models that predict recreation visitation and benefits for reservoirs at selected USACE districts.

c. Apply the models to estimate their impacts on resulting recreation visitation and benefits resulting from selected management actions.

2 Previous Work

A Role for Regional Recreation Demand Models in National Water Resource Planning

USACE projects operate under a wide range of hydrologic, demographic, and economic conditions. Because conditions rarely repeat themselves, information on recreation benefits that is used for management decision making must be correct under a wide variety of conditions to have maximum reliability. For example, suppose that the average visitor day of recreation at all USACE projects produces X dollars in NED benefits. Information on the numerical value of X is of some use to a planner. However, the value of X should be adjustable according to recreational preferences of the regional population, scarcity of substitutes, project operating conditions, and population density. Similarly, an additional acre foot of water held behind a USACE reservoir for 1 month may produce $1 in recreation benefits when the reservoir has few facilities, draws visitors from a limited market area, and has several recreational substitutes. However, an acre foot of water held at a reservoir with more facilities, a larger market area, and fewer substitutes may produce $25 in recreation economic benefits. For these reasons, information on recreation benefits should be adaptable to the wide range of conditions under which USACE projects operate.

For the above reasons, the USACE requires a model to estimate a regional recreation demand. For this study, a regional recreation demand model (RRDM) is a model that estimates NED recreation economic benefits produced at USACE projects that are accurate under a wide range of conditions, including management actions, project facilities, population demographics, and economic trends. Accomplishing this objective was the primary aim guiding the formulation and estimation of an RRDM.

Structure and Utility of Regional Recreation Demand Models

A few RRDM's have been developed by Government agencies, academic, and private interests. These models typically identify the determinants of

recreation use and use these determinants to develop predictive models for recreation use and benefits. Determinants of use may be related to resources, such as size of the water body or fishing success; demographics, such as the age and gender of the recreation market area or population size; and economics, such as distance, access, cost, income, and price of substitutes.

In 1983, the U.S. Water Resources Council (WRC) recommended developing regional recreation models to expedite evaluation of water resources projects. The WRC criteria for model development provide the purpose and scope of regional demand models.

Specifically, regional recreation models should yield an empirical estimate of demand applied to the particular project or site based on: (a) socioeconomic characteristics of market area populations; (b) qualitative characteristics and uniqueness of the recreation opportunities; and (c) costs and characteristics of substitute opportunities. Models should allow managers to generate recreation-use projections that vary with underlying determinants of demand and evaluate gains and losses in the study area.

Management of public reservoirs often requires that managers make economic tradeoffs between marketed commodities, such as hydropower, and nonmarketed commodities, such as recreation. Estimates of economic benefits based on observed behavior can provide information necessary for these tradeoff decisions. The travel cost model (TCM) provides information on the economic value of recreation opportunities commensurate with marketed outputs from water resource management policies.

The U.S. Water Resources Council (1983) requires that attention be given to maximizing net economic benefits in formulating water policies. The TCM provides a way to bring public recreation services, usually a nonmarketed commodity, into this analysis.

Information provided by the TCM can support several kinds of water resources planning decisions. A TCM can be used to determine the net economic value of an existing recreation site; provide estimates of the economic value of creating a new site or modifying an existing site; make more efficient allocation decisions among programs; explain visitors' travel behavior; and forecast changes in the use of a recreation site resulting from charging fees (or changing fees). Additional uses of regional travel models are described later in this chapter. A review of literature on travel cost models built since the 1960's shows three kinds of travel cost models: single-site models, multiple site-specific models, and regional models.

Single-site models

Early travel cost models were typically specified only for single-destination visits to a single site. Such a model is useful only for a limited number of resource management issues, such as the current per-day or per-trip value of

recreation under existing water and facility levels. The demand function can only reflect distance to the site and demographics of the visitors. Because all visitors to any given site experience the same reservoir level and amount of facilities, a separate variable cannot be estimated for these site characteristics, as they do not vary across visitor origins. If the analyst wishes to estimate how recreation use and benefits change with the addition of new recreation facilities or by maintaining a higher or lower than historical average reservoir water level, a single-site model may be of little use. This is because a single-site model only reveals average behavior under the current average conditions at this single site.

Predictions of the single-site model are based on travel costs from each zone of visitor origin in the market area to the site destination. Because a site-specific travel cost model predicts visitation based on variables unique to that site, it has limited capability to accurately transfer visits and benefit predictions to other sites. The only way to transfer predictions from one site-specific travel cost model to a different site is to find a travel cost model estimated for a similar site.

Transferring an existing single-site model to an unstudied target site requires the use of the "most similar site" method. Application of this method requires access to a known estimated price elasticity applied to a per-capita use model as a function of travel costs. Price elasticity is the percentage reduction in use with a 1-percent increase in travel cost due to distance from the destination site. Thus, if price elasticity were known to be -3.0, a 1-percent increase in travel cost could be assumed to reduce visits by 3 percent. Additional details on price elasticity and other economic concepts are presented in Chapter 4 of this report.

WRC's Principles and Guidelines (U.S. WRC 1983, p 73) discuss application of travel cost models to a target site for which there are no existing estimates of price elasticity. For a single-site model, one presumes that the facilities and other characteristics in comparing one site to the next are what make the price elasticities unique. The analyst must decide which existing site is most similar to the target study site. Mechanically, the analyst selects the most similar site, uses the estimated elasticity, and applies it to the target site. Per-capita use estimates are then computed for the target site from each zone of origin in the market area. Results of per-capita visitor use estimated in this manner are multiplied by population in each zone. The result produces an estimate of total visits. Recreation benefit is estimated by computing the increase in per-trip travel costs from any zone of origin needed to reduce that zone's visits to zero. An important limitation in implementing the similar-site method is the subjectivity inherent in attempting to match conditions at the target site to those at the most similar site.

Multiple-site models

A site-specific multiple-site model is an improvement to the single-site specific model described above. The site-specific multiple-site model attempts to predict demand at each of several sites in a region. Predicted demand is based on travel distances from several zones of origin in the market area to each site. This model is considerably more ambitious than the single-site model because it accounts for prices to substitute sites as a demand predictor, not just the price to the given site. Burt and Brewer (1971) conducted the classic study of this type, and similar models have been estimated more recently. One example is the model estimated for water-based recreation in a three-county region in New Mexico (Ward 1989). Despite their desirability, use of such models still requires the analyst to employ the most similar-site method when predicting demand and benefits at an unstudied site. The analyst still must make a subjective decision on which of those sites in the region has characteristics and travel distances that most closely approximate the target site. The strength of the multiple site-specific model is that it predicts demand for all sites in the region for which the study was done. Unfortunately, the model is not directly applicable to other unstudied sites of interest to managers. Moreover, even in the site-specific multiple-site model, looking for the similar site from which to transfer predictions to a target site introduces unavoidable arbitrariness. For this reason, USACE planners required something more versatile for the present study than the various site-specific models.

Regional models

Regional models offer considerably more to managers than either the single-site or multiple-site specific models. By combining visitor data from several visitor origins with varying demographics and from several reservoirs that have different amounts of recreation facilities and different surface acres, one can observe how visitors change their use rates in the face of more or less facilities, more or less water, or changes in demographic patterns. Thus, a more complete demand equation can be estimated that contains coefficients for reservoir surface acres and the quantity of recreation facilities and visitor levels. For example, the demand equation might be

$$\begin{aligned} TRIPS_{ij}/POP_i = {} & B_0 + B_1(DIST_{ij}) + B_2(INC_i) + B_3(SURAC_j) \\ & + B_4(TABLES_j) + B_5(SUB_i) \end{aligned} \tag{1}$$

where

TRIPS = trips from visitor origin i (1=1,..n) to site j (j=1 to m)

$DIST_{ij}$ = round trip distance form visitor origin i to site j

INC_i = income of visitors living in origin i

$SURAC_j$ = the average recreation season surface acres at site j

$TABLES_j$ = the number of picnic tables at site j

SUB_i = the extent of substitutes facing origin i visitors

The parameters B_0 through B_5 are constants interpreted as the incremental effect on TRIPS resulting from an increase of one in its variable.

With this model that combines facility, demographic, and substitute factors, the analyst can predict how visits to any one of the sites would change with the addition of the right-hand side variable. For example, B_4 is the additional trips per capita with the addition of one picnic table. The same interpretation holds for changes in water management actions that result in a change in surface acres or outside forces that affect future changes in demographic factors or substitutes.

Regional models estimate recreation benefits under existing conditions, and they can predict how use and benefits change with changes in management-controlled site variables. These models can be used to simulate effects on recreation use and benefits resulting from management actions at USACE projects.

A major advantage of RRDM is that it can provide an estimate of recreation use and benefits at a target site even though the target site does not match perfectly any of the existing sites used to estimate the model. This is possible because the regional demand equation allows analysts to estimate recreation use and benefits for numerous combinations of facilities at the target site not directly observed at the existing sites used to fit the model.

As long as the facilities at the target site lie within the range of observed facilities at the existing sites in Equation 1, managers can estimate the effects of changes in surface acres and picnic tables because there are coefficients reflecting the effects of these variables. Thus in principle, an unstudied USACE site can be described by a combination of its location ($DIST_{ij}$), its surface acres ($SURAC_j$), and its facilities (here illustrated by $TABLES_j$). Similarly, a new market area can be described by its population (POP_i) and substitutes (SUB_i).

In summary, an RRDM reduces the subjectivity in applying site-specific models to unstudied sites, unstudied market areas, or unstudied management actions at studied sites.

Comparisons of Site-Specific and Regional Models

Applications of RRDM to USACE projects provide a resource to identify the project attributes and user characteristics that determine recreation use at projects and project substitutes. An RRDM also predicts changes in recreational use. Finally, an RRDM translates the changes in recreation use to changes in benefits for management actions of interest.

First, an RRDM is generalizable to a wide range of management actions, site locations, visitor populations, and substitute opportunities. By contrast, site-specific models have little generalizability beyond conditions observed at that site.

Next, an RRDM generalizes patterns of observed behavior to a wider range of potential future onsite conditions than is possible with site-specific models. Included are natural conditions such as brought about by drought not previously observed at a given site. Also included are USACE management actions such as modifying reservoir levels, improving fish habitat, or improving various project facilities.

Third, the RRDM can be used to estimate effects of management actions made by managers not in the USACE. Examples include stocking fish by a state conservation agency or a state parks department adding picnic tables or camping areas at a USACE project.

Additionally, an RRDM has a greater potential for accurately transferring predicted visits or benefits to unstudied sites in the study region or at unstudied regions. The potential for accurate transfer of the RRDM is especially improved if measured value of facilities at the unstudied target sites and demographic characteristics at the unstudied market areas are numerically bracketed by those already studied.

Fifth, an RRDM is preferable to a site-specific model because it bypasses the subjectivity inherent in selecting a similar project at which to apply the model. This reduction in subjectivity reduces a potentially important source of investigator bias.

Finally, use and benefit predictions at target sites or outside operating conditions at existing study sites are more likely to be accurate than site-specific models. This greater accuracy is expected because an RRDM is based on observed behavioral responses to a wide variety of operating conditions at numerous sites throughout the region.

Performance Standards for a Regional Recreation Demand Model

An RRDM aims to predict demand and benefits of potential management actions at one or more existing study sites or at unstudied target sites. Overcoming the limits imposed by site-specific models requires that a regional model should meet several criteria, four of which are described in WRC's Principles and Guidelines (U.S. WRC 1983, p 67):

a. The RRDM should be based on measurable demographic characteristics of market area populations.

b. The RRDM should be based on measurable factors that characterize the uniqueness of recreation opportunities at the site.

c. The model should rely on measurable costs and characteristics of substitute opportunities in the region facing area populations.

d. Demand and benefit projections over time and over the range of potential management actions should be based on projected changes in underlying determinants of demand.

If an RRDM meets the above four criteria, it allows managers to evaluate a wider range of possible management actions quantitatively, based on the wide range of information from which the model was estimated.

Previous Work on Travel Cost Models

Early USACE work on regional models performed by Brown and Hansen (1974) demonstrated how regional models could be developed and used to predict visitation. Using day-use visitation data from U.S. Army Engineer District, Sacramento, and U.S. Army Engineer Division, Southwestern, projects, regional models were developed. This model has a wide range of applications, which is typical of regional models. The day-use estimator model related the amount of day-use visitation to a project from an origin (the dependent variable) to the independent variables of (a) the ratio of population of the origin to the distance to the project, (b) the attributes of the project (taken to be the water surface acreage of the project), and (c) the availability of substitutes for the project, measured as the index of the substitutes. This model used the pool acreage as a main measure of the attributes of the project.

A person's decision to visit one project rather than another is based on a number of factors, many of which are unique to the person. Modeling all these factors algebraically in a way that would be valid for all individuals is impractical. However, some simplifications can be made. The need to account for availability of substitutes when predicting visitation is usually

simplified by specifying some simple variables used to determine whether a visitor from a given origin will go to one project over another. In the day-use model, this was accomplished by an index representing the attractiveness of the available substitutes to the project. The substitute index is based on a project's attractiveness, using the size of the reservoir pool. The substitute index in the model was determined by summing the ratios of a substitute's pool size to distance from the origin of interest.

A travel cost model was developed to allocate recreation use to 83 reservoir, lake, and river areas in California (Wade et al. 1989a). The four activities of boating, fishing, picnicking, and swimming are considered in the model. The model was a gravity travel cost model, with recreation trips from an origin allocated to one project over another based on criteria related to the attractiveness of a project, capacity of the project, and distance from the project to the origin. The number of trips for different activities were estimated from a household survey of visitor preferences. A significant limitation of this study is the lack of recreation use surveys at recreation areas and data on observed origin-destination travel patterns.

USAE District, Rock Island, developed a model that estimates the benefits associated with the 3 reservoirs and 27 Mississippi River recreation sites (O'Keefe 1985). The model is included here to illustrate the type of modeling work that can be accomplished using data collected in recreation-use surveys. A limitation of this study is that the demand model does not consider substitutes and is not correctly specified for a regional model, because it is not transferrable to regions with different substitutes for USACE projects.

Recreation-use surveys were conducted during the 1983 recreation season. Market areas were determined for each site, the market areas containing 90 to 99 percent of the sample visits. Visitor zone-of-origin data (based on zip codes) from the surveys were used to develop 10-mile-wide zones. The zones used to develop a TCM for determining recreation benefits for each reservoir or river site. Income, employed labor force, and population over 18 years of age for each zone were drawn from a database of residential zip code demography for 1985, and incorporated in the TCM.

The Brown and Hansen (1974) model is the most useable existing RRDM. The Brown Hansen model was developed using observed origin-destination data, while the Wade model used activity preferences from a household survey to determine demand for recreation. Substitutes utilizing measures of attractiveness related to quality and capacity of the projects were incorporated in both models.

The Rock Island District model (O'Keefe 1985) is based on recreation-use data collected for and specific to a recreation reservoir or river site. Though not a regional model, the Rock Island District model is commendable for its use of the recreation survey data to develop benefit estimators for each project. The survey data already collected by the Rock Island District could be used to develop a regional model. While these models were effective in

addressing specific objectives for the Rock Island District, the models were not designed to be of sufficient scope to address the broad range of national planning and operations issues, project characteristics, and geographic settings that confront potential USACE management actions.

The final RRDM identified is the one described by Cole et al. (1990) and Cole and Ward (1994) in which a regional travel cost model is fit for 132 fishing waters in New Mexico. Demands and benefits from numerous fishing management actions are estimated. The data used to fit the model are origin destination telephone survey data of anglers at 132 fishing sites comprising about 90 percent of New Mexico's fishing.

As seen in the above discussion, RRDM's are not a new idea. However, this study aims to extend approaches used in previous models. It also aims to evaluate the extent to which models developed for a specific region can be generalized to other regions. Finally, it hopes to determine if models developed for a particular set of planning or operation questions can be generalized to other planning or operation questions not yet studied.

3 Database Assembly

An important goal used to organize the data collection effort was that transfers of estimated demand and benefits should be valid under a wide range of future management actions. Several steps were taken to accomplish that end.

An early step was to specify the model's scope (dimensions) to produce sufficient resolution to cover the maximum range of potential management actions of interest to the USACE consistent with available data. Identifying the model's dimensions allows the model to correctly measure demand and benefits resulting from a wide range of future management actions. For this study, the dimensions were time period, project location, and county of visitor origin.

After the model's dimensions were selected, important variables that predict recreation demand were identified. Variables were selected according to what economic theory suggests significantly affects recreation demand and benefits. Four classes of variables included resource user demographics, travel costs from zone to site, site facilities, and substitute opportunities. Several variables were selected within each of those four classes. More variables than necessary within each class are selected because not all theoretically correct variables in each class typically enter a regression model due to collinearity or other statistical problems.

Attempts were made to select USACE projects that produced data with wide ranges in the variables, as the data used to fit the demand model should have a wide enough range in each variable to bracket applications of that variable to future management questions. For example, reservoir levels in USACE projects vary over the dimensions of project location and time period. Reservoirs varied in size from large to small. Water levels at each reservoir vary from high to low. The USACE wishes to estimate the consequences on visitation and benefits of varying water levels from full to empty at USACE projects around the country. For this reason, sampled water levels should vary widely at each project, and it should vary across a wide range of project sizes. A dataset with little water variation at each project would tell little about the effects of management plans that vary water at the project level. Conversely, a dataset collected at mostly average-sized projects offers little useful information about the impact on recreation behavior of actions implemented at large or small projects.

The model was specified with algebraic functional forms to avoid producing absurd results from extreme management actions implemented outside the range of past observed data. On the surface, it is expected that linear models should cause little trouble. However, linear models can predict negative visits for extreme values of the explanatory variables. For this and other reasons described subsequently, log-log models are used for this study.

Attempts were made to formulate models consistent with economic theory. Algebraic forms for models were specified that account for choices and constraints that face resource users. Models should correctly account for substitution relationships, site characteristics, and visitor demographics. Models based on poor economic theory cause computed benefits to mean little, especially outside the range of observed data.

Practically, functional forms for economic benefit models should account for diminishing incremental visitation and benefits from improvements. That is, management actions that improve facilities should not increase benefits or visits at an increasing rate. Models should also account for effects of substitute opportunities and limited incomes that constrain visitation in the region.

Models that are consistent with visitors' budget constraints are likely to produce the most coherent results over the widest range of management actions modifying resource qualities or quantities. That is, economic benefit models should be consistent with the microeconomic theory of consumer choice. Unfortunately, data needed to estimate such theoretically correct models (complete demand systems) are typically expensive and were not available for the present study. Considerable future work remains to be done on developing performance standards for complete demand/benefit systems.

It is desirable to pool data where possible, as benefit models estimated by pooling data over all available dimensions and sample units will have greater potential to transfer to the widest range of future management actions. For example, an RRDM is expected to transfer to a wider range of national conditions if estimated from a three-region dataset than from a single region. The present study assembled visitation datasets for the U.S. Army Engineer Districts, Sacramento, Little Rock, and Nashville. Lacking further knowledge for USACE projects outside those three districts, estimated models are expected to have the greatest transferability to other projects nationally if models are fit by pooling all districts' datasets.

Resources Needed to Assemble Database

Assembly of this database required considerable organizational effort and a clear sense of where we wanted the model to go. Approximately two full-time person years were spent over a 1-year period in assembling it. In the completed dataset, each record consisted of an observation on one county for 1 year for one USACE project.

For each county, data were required for all the important demographic variables that could influence visitation at a project. These variables included total population and various demographic indicators. Also, included was an indicator of total substitute surface acres from each county to all locations within 250 miles of that county. With more than 800 counties in the three-district database, constructing the substitute surface area variable alone required 4 months of full-time work. The formula for the substitute index is defined mathematically later in this chapter.

For each project, data were required on all the permanent facilities that were expected to significantly affect visitation. Fortunately, access to the USACE Natural Resources Management System (NRMS) data retrieval system made these variables easy to find. However, data was also needed on water levels, water quality, and fish populations from previous fish stocking. Obtaining these data required numerous calls to the USACE district offices and state game and fish departments. Total time spent was about 3 months.

Travel costs were computed from each origin to each project using the software PC-Miler®. Several hundred thousand combinations were processed. Organizing all the data into a single useable dataset required considerable programming in LOTUS 1-2-3® and SAS®, as illustrated in Figure 1.

USACE District Selection and Criteria

Districts were chosen according to several criteria. First, each district needed to have good origin destination (OD) data. Additionally, we selected two districts that were close enough in recreational opportunities and visitor preferences to permit a plausible benefit transfer. Similarly, the third should be quite different from the other two to test the limits of the model's power to transfer predicted visits and benefits. Three total districts were chosen because resource economists at three land grant universities (New Mexico, California, and Kentucky) made up the modeling team. The USACE districts selected that best met the criteria described were Sacramento, Nashville, and Little Rock.

Dependent Variable

The dependent variable defined for all models is an estimate of total market area visitation, for both day use and camping, from county i to site j during year k. USACE visitor surveys provided visitor samples. However, sampled visits cannot be used directly as dependent variables because projects were surveyed at significantly different sampling rates. Failure to account for different sampling rates would result in higher visit predictions at some projects merely because they were surveyed at higher rates.

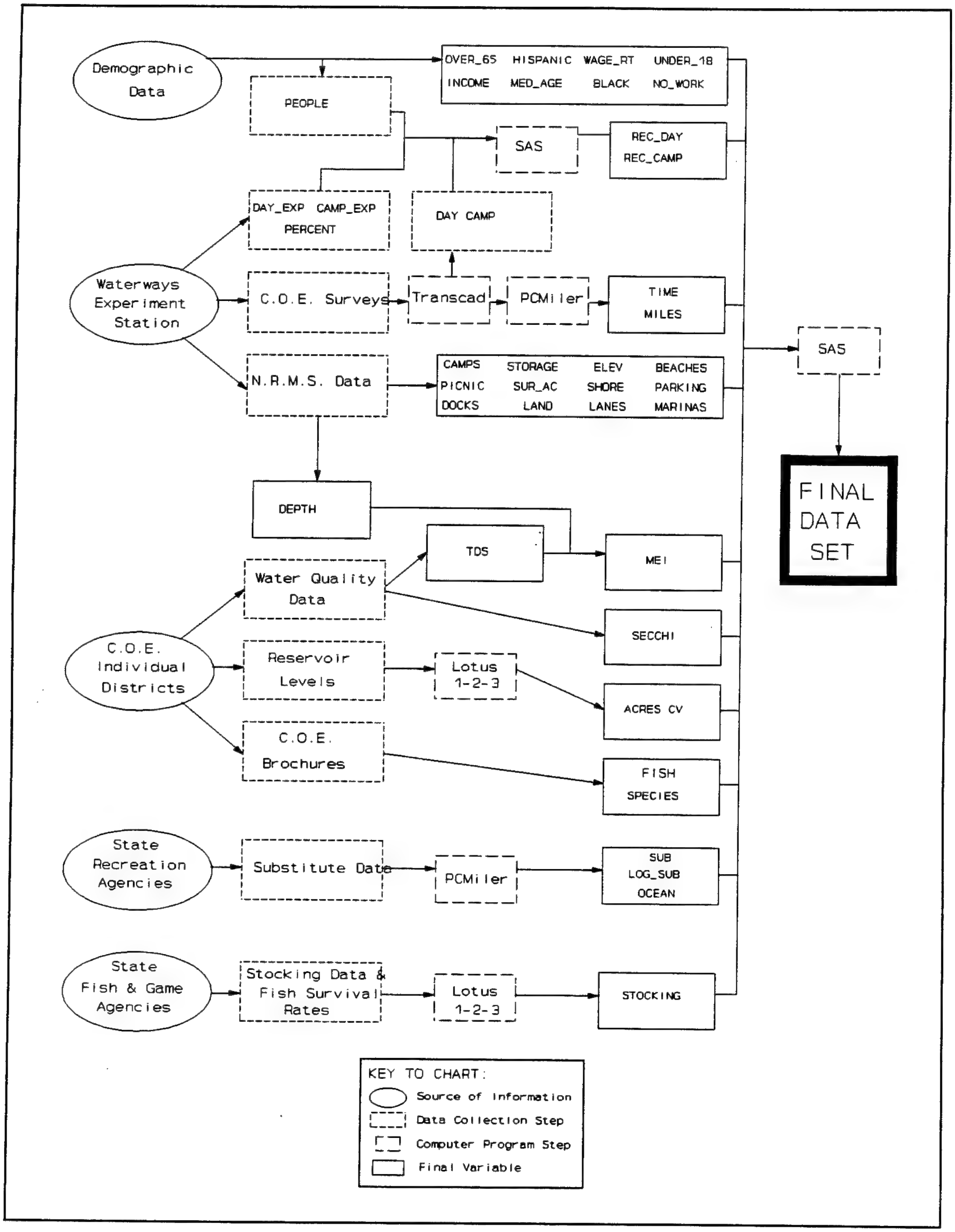

Figure 1. Flowchart of database development

Sampling rate differences across projects were corrected by using variable sampling expansion factors. Sample expansion factors are defined as the ratio of total estimated visits at a project to visits sampled by the USACE survey. By multiplying the sampled visits from a county by the appropriate sample expansion factor, an estimate of total visitation from the county is obtained.

The next section details the steps to estimate total visits. Management of the visitor survey data and calculation of the sample expansion factor are described. These steps permit the dependent variable to be computed.

Project visitor counts

It was known for some time in advance of the model estimation that the dependent variable would be related in some way to total project-level visit counts. A project visit was selected as the dependent variable for modeling purposes and is defined as the entry of one person into any recreation area on a USACE project to engage in one or more recreation activities. A visit is simply a head count of a visitor. A trip to a project by one person to go fishing for 1 hour and a 2-week camping trip to a project by another person each count as one visit.

Visits were further divided into camping visits and day-use visits, because each was expected to reveal significantly different behavior. A required model input is historic camping and day-use visit records for the period 1983 through 1986. Project visitation data as recorded in the USACE NRMS were obtained from each USACE district office.

Records of total day-use and camping visits at the project level were not maintained for the period of interest, 1983 through 1986. Prior to 1987, visitation records were maintained in recreation days, not visits. Visitation records after 1987 were maintained in visits. This discrepancy required the transformation of recreation days to equivalent visits for years prior to 1987. The transformation takes several steps and is described below.

Begin by recognizing the following relationship between total recreation days, day-use visits, and camping visits

$$RECDAYS_{TOTAL} = (1.0 * VISITS_{DAY}) + (2.43 * VISITS_{CAMP}) \tag{2}$$

where

$RECDAYS_{TOTAL}$ = annual total project recreation days summed over day-use and camping visits reported in NRMS data system

$VISITS_{DAY}$ = annual total project day-use visits to be solved for

$VISITS_{CAMP}$ = annual total project camping visits to be solved for

A day-use visit contributes 1 recreation day toward the recreation day total. A camper visit contributes an average 2.43 recreation days toward the recreation day total, because the average length of stay per camper visit is 2.43 days (Jackson and Rogers 1990).

The objective is to solve for $VISITS_{DAY}$ and $VISITS_{CAMP}$ because project level totals for each are required for the RRDM, while neither is known directly.

Define total visits over day users and campers as $VISITS_{TOTAL}$, which is defined as

$$VISITS_{TOTAL} \equiv VISITS_{DAY} + VISITS_{CAMP} \tag{3}$$

The USACE records percentage of total visits that consist of camping in the NRMS data set. This percentage permits calculation of total camping visits and total day-use visits using the following two formulas

$$VISITS_{CAMP} = VISITS_{TOTAL} * (CAMP\%/100) \quad \text{and} \tag{4}$$

$$VISITS_{DAY} = VISITS_{TOTAL} * ((100 - CAMP\%/100) \tag{5}$$

where

CAMP% = percent of total visits that consist of camper visits recorded in the NRMS database

A system of three equations can now be specified using Equations 2, 4, and 5. For each project, the system consists of three unknowns: $VISITS_{TOTAL}$, $VISITS_{CAMP}$, and $VISITS_{DAY}$. Known data available from the NRMS database for each project are $RECDAYS_{TOTAL}$ and CAMP%.

The three equations are solved for as follows: First, solve for $VISITS_{TOTAL}$. Substitute Equation 5 into Equation 2 to produce

$$\begin{aligned} RECDAYS_{TOTAL} = {} & VISITS_{TOTAL} * ((100 - CAMP\%)/100) \\ & + [2.43 * (VISITS_{TOTAL} * (CAMP\%/100))] \end{aligned} \tag{6}$$

Equation 6 can be used to compute the total visits, $VISITS_{TOTAL}$. Moving $VISITS_{TOTAL}$ to the left-hand side of Equation 6 allows expression of total visits in terms of known data

$$VISITS_{TOTAL} = (RECDAYS_{TOTAL} * 100) / [(100-CAMP\%) + (2.43 * CAMP\%)] \quad (7)$$

Once total visits are computed, its solution can be substituted into Equations 4 and 5, giving the values of $VISITS_{CAMP}$ and $VISITS_{DAY}$ as in terms of known data. Results are

$$VISITS_{CAMP} = [(RECDAYS_{TOTAL} * 100) / [(100-CAMP\%) + (2.43 * CAMP\%)]] * [CAMP\%/100] \quad (8)$$

$$VISITS_{DAY} = [(RECDAYS_{TOTAL} * 100) / [(100-CAMP\%) + (2.43 * CAMP\%)]] * [(100-CAMP\%)/100] \quad (9)$$

The values of $VISITS_{CAMP}$ and $VISITS_{DAY}$ are completely expressed in terms of the known NRMS data by solving Equation 9.

Table 1 lists the calculated values of $VISITS_{CAMP}$ and $VISITS_{DAY}$ for all sites and all years included in the analysis. Results of the regional recreation demand models estimated for this report are based on total day-use and camper visits as computed in Equation 9. However, translations into visitor hours or recreation day can be calculated from USACE formulas if needed.

Performing the translation from visit to visitor hour or recreation day requires information on the length of stay for day users and campers. The preferred method for obtaining this information is direct surveying at the projects under study. These statistics are routinely reported in the standard VERS Load Factor Report. If survey results are not available, then consider using the national average length of stay of 3 hours for day users and 2.43 days or 58.32 hours for campers. These values can be used to convert visitation and benefit calculations derived from the RRDM to visitor hours.

Visitor origin destination data

The dependent variable for all models is an estimate of total annual market area visitation from county *i* to site *j* during year *k* ($VISITS_{ijk}$); it is estimated for all counties within a specified market area, discussed in Chapter 4. The total visitation specification is preferred to a per-capita visitation dependent variable by being less restrictive (Rosenthal 1987; Knetsch, Brown, and Hansen 1976). Use of a per-capita dependent variable, i.e., total visits divided by total population, restricts the exponent on population to be exactly 1.0. Rather than imposing such a restriction, use of total visitation as an independent variable tests whether visitation increases proportionally as population increases. Rural counties, common for USACE projects, may exhibit different recreation use patterns than more urban counties. An exponent of less than 1.0 on population indicates that visitation rates per unit of county

population are higher in less populated counties. An exponent of greater than 1.0 reveals that urban populations, on a per-capita basis, contribute more visits to the project.

All data on visitation were collected from USACE exit surveys conducted during 1983-1986. Surveys were conducted during the years 1983 through 1985 in the Sacramento District, 1983-1986 in the Nashville District, and 1985 in the Little Rock District. For the Sacramento and Nashville Districts, not all projects were surveyed in each year. A list of the individual sites and the years in which they were surveyed is given in Table 2. Additional details on the surveys are described in Dames and Moore and Perales (1992).

At the end of their trips to projects, survey respondents were asked to indicate their zip code of origin. The Little Rock District surveys included zip codes of origin for 48,629 day-user surveys and 4,724 camper surveys. The Nashville District produced 17,562 day-user surveys and 2,094 camper surveys. In the Sacramento District, 81,306 day-user surveys and 17,040 camper surveys indicated zip codes. Thus, the size of the OD dataset is extensive by conventional standards of travel cost recreation studies.

A national zip code county directory was used to assign a county and state to each survey zip code of origin. Any national database that cross references zip codes and associated counties and states can be used for this purpose. Numerous similar databases are widely available from commercial vendors at costs under $500. Surveys were aggregated to obtain the total surveys sampled by day-use and camper categories from county i to site j during year k for all counties of origin producing at least one sample survey.

Using sample expansion factors

Sample expansion factors unique to each project and year were necessary to magnify sampled visitation to an estimate of total visitation. This magnification was necessary because visitor surveys at each project intercepted a different proportion of total visits. Failure to account for different sampling rates across projects or years results in the error of greater predicted visitation to a project or year simply because it was sampled at a higher percent of total visitation.

The process of sample expansion begins by estimating actual total day-use and camper visitation numbers for each site during each year as explained previously in this chapter. Visitation data were obtained from two sources: the individual USACE districts and the Waterways Experiment Station (WES). The object was to obtain an estimate of the total number of day-use and camper visitors during the surveyed years.

Based on the presumed correct total use estimates and assuming a random sample, sampled visitation totals for each county i to site j in year k can be multiplied by the appropriate expansion factor. The estimate of total visitation

from origin i to site j in year k is then corrected for the effect of different sampling rates at different projects.

Calculation of sample expansion factors is based on the ratio of total visitation to sampled visitation, as described previously. The formula used for computing sample expansion factors is

$$SMPL\_EXP_{jk} = (VISITS_{JK} / \textstyle\sum_i SAMPLED\_VIS_{ijk}) \tag{10}$$

where

$VISITS_{jk}$ = estimate of total visitation

$SAMPLED\_VIS_{ijk}$ = number of visitors sampled over counties i by exit surveys at project j during year k

The sample expansion factor is computed for all projects and years. Separate sample expansion factors are calculated for the day-use and camping models.

The sample expansion factor calculated in Equation 10 for each project and year is used to allocate that total among the various counties of origin i. Its formula is

$$TOTAL\_VIS_{ijk} = SAMPLED\_VIS_{ijk} * SMPL\_EXP_{jk} \tag{11}$$

That is, the percent of total visitation to allocate among counties of origin is determined by the distribution of origin counties intercepted by the survey. The absolute totals are determined by total visitation estimation by project and year. Sample expansion factors in this study range from 20 to over 7,000. In the Nashville District, sample expansion factors averaged nearly 3,000, i.e., the sample was a small part of total visits. In the Little Rock District, a greater proportion of visitors were intercepted by the survey, which resulted in sample expansion factors averaging around 1,000. The highest percentage of visitors were intercepted by the survey in the Sacramento District, where the average sample expansion factor was around 230.

Discussion now turns to a problem widely recognized in travel cost demand studies, namely what to do with the county zones of origin producing no sampled visitors. Where no visitors are sampled from county i to site j during year k, multiplication by the sample expansion factor will result in zero calculated $TOTAL\_VIS_{ijk}$. The number of counties with zero sampled visits is considerable, at over 70 percent for the Nashville District. Because $SMPL\_EXP_{jk}$ tends to be large, estimated county visitation totals, $TOTAL\_VIS_{ijk}$, range from zero to several thousand.

A closely related problem arises when attempting to calculate the natural log of a zero variable, which is required for the log linear functional form used for this study. Since the log of zero is undefined, an adjustment of these zeros is necessary, if for no other than mechanical reasons. One possibility is to redefine zone of origin until all zones show positive sampled visitation (Rosenthal et al. 1986). Unfortunately, grouping counties into larger zones reduces the variability of demographic variables and travel costs, which throws out valuable information needed to separate the influences of the different demand predictors. Many researchers have remedied this problem by adding a small constant to the zero visitation number. However, the approach taken in this study involves rethinking the process of extrapolating from the sample to the population.

We begin by differentiating between the observed sample value of visits ($SAMPLED\_VIS_{ijk}$) and the expected sample value ($E(SAMPLED\_VIS_{ijk})$) over several equivalent samples. The expected value of $SAMPLED\_VIS_{ijk}$ over many samples is obtained by observing the actual total number of visitors from county *i* to site *j* during year *k* and multiplying by the proportion of visitors surveyed. In this study, the expected value of $SAMPLED\_VIS_{ijk}$ is unknown because county visitation totals are unavailable.

The problem of zero sampled visits can be illustrated by example. Suppose county *i* sends 270 visitors to site *j* during a year. Also, assume that 1 out of every 600 visitors to site *j* are sampled. This produces a sample expansion factor of 600. The expected surveyed visitors from county *i*, $SAMPLED\_VIS_{ijk}$, is

$$E(SAMPLED\_VIS_{ijk}) = 270 * (1/600) = 0.45 \tag{12}$$

A value of 0.45 for $SAMPLED\_VIS_{ijk}$ is unobservable, because $SAMPLED\_VIS_{ijk}$ must be an integer. With the integer requirement, an observed value of 0 is expected if the expected value is less than 0.5 and a value of 1 if the expected value is greater than 0.5. Thus, in the above example, the value of $SAMPLED\_VIS_{ijk}$ is 0. However, because the known true value of $TOTAL\_VIS_{ijk}$ is 270, some error has been introduced into the analysis through this sample method. The procedure described below attempts to reduce such errors.

If the visitation sample is random across several counties, then surveys are no more likely to encounter visitors from any particular county of equal population demographics, travel costs, and substitutes, than by chance alone. In this case, any observed value of 0 for $SAMPLED\_VIS_{ijk}$ arises because ($0 < E(SAMPLED\_VIS_{ijk}) < 0.5$). It follows that

$$E(TOTAL\_VIS_{ijk}) = E(SAMPLED\_VIS_{ijk}) * SMPL\_EXP_{jk} \quad \text{and} \qquad (13)$$

$$0 < E(TOTAL\_VIS_{ijk}) < (0.5 * SMPL\_EXP_{jk})$$

The use of Equation 11 above, when the observed $SAMPLED\_VIS_{ijk} = 0$, produces a result of 0 for $TOTAL\_VIS_{ijk}$. However, from Equation 13 it is known that $E(TOTAL\_VIS_{ijk})$ ranges between 0.0 and $(0.5 * SMPL\_EXP_{jk})$.

An important question is whether $TOTAL\_VIS_{ijk} = 0$ is the best estimate of $E(TOTAL\_VIS_{ijk})$. In repeated sampling, estimates of $TOTAL\_VIS_{ijk}$ are expected to converge to $E(TOTAL\_VIS_{ijk})$. If $(E(TOTAL\_VIS_{ijk}) > 0)$, one will occasionally observe $(SAMPLED\_VIS_{ijk} = 0)$ in repeated sampling.

However, for any given year, only one sample is available for each county by year for the present analysis. In the Little Rock District, surveys were conducted in only 1 year. Even in the other districts, a maximum of 3 years were surveyed for any particular site. One factor not incorporated by the formula in Equation 11 is that observed 0 values of $SAMPLED\_VIS_{ijk}$ become more meaningful as the sampling rate increases.

A second example is presented for the sake of comparison. Suppose that instead of sampling 1 of 600 visitors, 1 of 2,000 is sampled. For this smaller sampling rate, the $E(SAMPLED\_VIS_{ijk})$ is

$$E(SAMPLED\_VIS_{ijk}) = 270 * (1/2{,}000) = 0.135 \qquad (14)$$

Again, one would expect to observe $SAMPLED\_VIS_{ijk} = 0$. Assuming a random sample in both cases, one can figure the expected bounds for $TOTAL\_VIS_{ijk}$. When 1 of 600 visitors are sampled, the bounds are

$$0 < E(TOTAL\_VIS_{ijk}) < (0.5 * SMPLE\_EXP_{jk}) = (0.5 * 600) = 300 \qquad (15)$$

When 1 out of 2,000 visitors are sampled, the bounds are

$$0 < E(TOTAL\_VIS_{ijk}) < (0.5 * SMPL\_EXP_{jk}) = (0.5 * 2{,}000) = 1{,}000 \qquad (16)$$

Thus, tighter bounds can be placed on the expected range of $TOTAL\_VIS_{ijk}$ as the sampling rate is increased.

If $TOTAL\_VIS_{ijk}$ is always set to 0 when $SAMPLED\_VIS_{ijk} = 0$, then the assumption is made that $E(TOTAL\_VIS_{ijk})$ always falls at the lower limit of its range. This unrealistic assumption will cause a biased estimate of visitation

and benefits and will also bias the estimated effects on visits and benefits of management actions.

Lacking good information on the distribution of visitors when $SAMPLED\_VIS_{ijk} = 0$, a good estimate of $E(TOTAL\_VIS_{ijk})$ when $(SAMPLED\_VIS_{ijk} = 0)$ is the midpoint of its expected range

$$\begin{aligned} E(TOTAL\_VIS_{ijk}) &= 0.5 * (0.5 * SMPL\_EXP_{jk}) \\ &= (0.25 * SMPL\_EXP_{jk}) \end{aligned} \tag{17}$$

Thus, the estimated value of visits produced by a county by project and year, $TOTAL\_VIS_{ijk}$, should, on average, be set equal to 0.25 times the sample expansion factor when $SAMPLED\_VIS_{ijk} = 0$. This conclusion is independent of the population of the county or any other demographic substitute or project facility factors, because the observed zero and sample expansion factor are the only available information.

This method of analysis assumes that on average $E(TOTAL\_VIS_{ijk}) = (0.25 * MPL\_EXP_{jk})$ when $SAMPLED\_VIS_{ijk} = 0$. If the exact distribution of $E(TOTAL\_VIS_{ijk})$ when $SAMPLED\_VIS_{ijk} = 0$ is known, a different multiplication constant is recommended. However, if any symmetric statistical distribution within this range occurs, then $E(TOTAL\_VIS_{ijk})$ converges to $(0.25 * SMPL\_EXP_{jk})$ when $SAMPLED\_VIS_{ijk} = 0$. Even if the distribution is close to symmetric, $E(TOTAL\_VIS_{ijk})$ converges to approximately $(0.25 * SMPL\_EXP_{jk})$ and not to 0.

Setting $TOTAL\_VIS_{ijk} = (0.25 * SMPL\_EXP_{jk})$ when $SAMPLED\_VIS_{ijk} = 0$ is more accurate than setting $TOTAL\_VIS_{ijk} = 0$ as described in Equation 11. This method also accounts for differences inferred by different sampling rates, as the value of $SMPL\_EXP_{jk}$ varies with the sampling rate.

Using the original value of $TOTAL\_VIS_{jk}$ as given in Equation 11 results in

$$\sum_i TOTAL\_VIS_{ijk} = VISITS_{jk} \tag{18}$$

where

$VISITS_{jk}$ = estimate of total visitation at site *j* during year *k* as calculated in Equation 8

However, if $TOTAL\_VIS_{ijk} = (0.25 * SMPL\_EXP_{jk})$ when $SAMPLED\_VIS_{ijk} = 0$ and $TOTAL\_VIS_{ijk} = SAMPLED\_VIS_{ijk} * SMPL\_EXP_{jk}$ if $SAMPLED\_VIS_{ijk} > 0$, it follows that

$$\Sigma_i \, TOTAL\_VIS_{ijk} > VISITS_{jk} \tag{19}$$

as long as 0 visits are observed from some counties. However, based on the available data and assuming a random distribution, the best estimate of $TOTAL\_VIS_{ijk}$ when sampled visits are positive is still ($SAMPLED\_VIS_{ijk}$ * $SMPL\_EXP_{jk}$). Because the difference noted in Equation 19 tends to be small for most practical applications (only 1 or 2 percent of total visits), the value of $TOTAL\_VIS_{ijk}$ when sampled visits are positive are left as ($SAMPLED\_VIS_{ijk}$ * $SMPL\_EXP_{jk}$).

A second method for estimating total visits from each county is to make a slight correction to maintain the equality in Equation 18. Thus, all values of $TOTAL\_VIS_{ijk}$ when $SAMPLED\_VIS_{ijk} > 0$ would be adjusted downward by a small fraction. This method considerably complicates calculating the dependent variable as the proportion of 0 sampled visits changes with each change in market area. Because the adjustment factors are quite small and made no significant difference in several preliminary estimated models, no adjustments were made.

For counties with 0 sampled visitors, the value of $TOTAL\_VIS_{ijk}$ is always reset to (0.25 * $SMPL\_EXP_{jk}$), regardless of the choice of market area. A rather detailed description of the justification in this decision follows.

Suppose the analysis is restricted to a particular market area such that some percentage of sample visitors is deleted. In this case, not all sampled visits would be used in Equation 10 in calculating the sample expansion factors. The total number of visits needed to expand to would be less than $VISITS_{jk}$. If the survey is a random sample, the proportions in the survey reflect the proportions of actual total visitation. Thus, to calculate the number of actual visitors to site *j* in year *k* within a given market area, the proportion of sampled visitation occurring within the market area is used. If the number of sampled visits from county i to site j during year k within the market area was $MKT\_AREA\_VIS_{ijk}$, this fraction is

$$FRACTION_{jk} = \Sigma_i \, MKT\_AREA\_VIS_{ijk} \, / \, \Sigma_i \, SAMPLED\_VIS_{ijk} \tag{20}$$

One would then expand the sampled visitation to equal ($FRACTION_{jk}$ * $VISITS_{jk}$) rather than unadjusted $VISITS_{jk}$. The appropriate sample expansion factor then becomes

$$SMPL\_EXP_{jk} = (FRACTION_{jk} * VISITS_{jk}) \, / \, (\Sigma_i \, MKT\_AREA\_VIS_{ijk}) \tag{21}$$

However, using Equation 20 to substitute for (Σ_i $MKT\_AREA\_VIS_{ijk}$), this becomes

$$SMPL\_EXP_{jk} = (FRACTION_{jk} * VISITS_{jk}) / (FRACTION_{jk} * \textstyle\sum_i SAMPLED\_VIS_{ijk}) \tag{22}$$

The term $FRACTION_{jk}$ in Equation 22 cancels out to obtain

$$SMPL\_EXP_{jk} = (VISITS_{jk} / \textstyle\sum_i SAMPLED\_VIS_{ijk}) \tag{23}$$

which is the same calculation obtained in Equation 10. Therefore in our analysis, we could make the strong conclusion that the sample expansion factor is independent of the size of the market area.

Creation of dependent variable: Merging project visitation and origin-destination data

An estimate of total visits was calculated for sampled visits in each county, project, and year. The variable $TOTAL\_VIS_{ijk}$, defined in Equation 11 was used as the dependent variable. The RRDM thus attempts to explain total visitation from any county to any project and any year by travel cost, various facility variables, substitutes, and various county demographic variables.

Translating individual visit data to county totals

For each vehicle interviewed for the USACE, information was gathered on number of persons in the vehicle and home zip code. An IBM PC based geographic information system software package, TRANSCAD®, was used to aggregate the total number of day-use and camping visits originating in each county in the market area. Using the TRANSCAD® software, visits from each zip code were assigned to the county in which that zip code is located. This process was repeated for each project, resulting in values of $SAMPLED\_VIS_{ijk}$ for both camping and day-use visitors for every county/ project/year combination included in the dataset.

Treatment of counties bordering projects

Because the exit surveys were intended to characterize visitation at representative access points at each project, the sampling frame was constructed to generate a random sample of visitors at each of those access points. Access points sampled at a given project were often located in more than one county. The large size and unusual shape of many projects meant that the sampled access points could be quite a distance away from some counties bordering the project. Residents of those counties may visit a project at a nonsampled access point located close to home, rather than travel to the more distant access point.

To mitigate this sampling bias at the bordering counties, all counties that border the project were lumped together to form one large zone of origin. Independent variables for this lumped zone were constructed by summing the population weighted average (where appropriate) of the individual county values. Therefore, population of the lumped zone equals the sum of the county populations, and travel distance equals the average of the individual county travel distances weighted by population. Equivalent measures were applied to the demographic variables from the individual counties surrounding the project.

Independent Variables

Introduction

Economic theory supported by past experience of recreation managers has shown that four classes of independent variables affect recreation visitation: demographic variables, site variables, travel costs, and substitutes. Demographic variables characterize zone-of-origin populations. There are several kinds of site variables, including installed site facilities, fishing quality, water quality, and water level variability. Travel cost plays an important role. The final factor is recreational substitutes. Information on each class of variables is used in the present modeling effort.

Demographic variables

Populations of visitor counties of origin are characterized by several demographic variables, which generally were obtained from U.S. Census sources. Because the dependent variable is visitation from county i to site j during year k, all demographic independent variables are ideally defined specific to county i during year k. However, census data is typically unavailable at a county level for every year. Because the onsite surveys were conducted between 1983 and 1986, the 1980 census was the most appropriate source to use for demographic data. Also, data from the 1990 census were unavailable when the demographic database was constructed during 1991.

County population was the only demographic variable available from the U.S. Department of Commerce for every year in the 1983-through-1986 period. The *USA Counties* database on CD-ROM provides estimates of county population on a yearly basis. Year-specific data on population seemed especially important because visitation rates at USACE projects can change during the period of analysis simply due to population changes. While many of the other demographic variables, such as income and unemployment, likely exhibited little change during the period of analysis, population did change in many counties. A yearly varying population variable also accounts for changes in population when applying the model results to years outside the study period.

Demographic variables for POPULATION and average county per capita income, INCOME, are used in all models. Other variables may induce multi-collinearity problems and are chosen according to the statistical contribution to the model performance. As described below, the average per-capita county wage rate, WAGE_RATE, is included in all models as part of the calculation of travel costs, and it is used to calculate the monetary costs of travel time. Additional demographic variables include the age structure and ethnic composition of the county.

Few consistent hypotheses regarding the influence of demographic variables on recreational visitation have been published. While population size should have a positive effect on visitation, visitation may not increase proportionally to population. As described earlier in this chapter, including population as an independent variable allows analysts to test for differences in recreational behavior between rural and urban counties. Depending on the type of reservoir, population could have an elasticity of greater or less than unity. For example, if rural counties visit USACE projects more often than urban counties on a per-capita basis, the elasticity of population is less than 1.0.

Similar ambiguity exists for the effect of other demographic variables on recreational visitation. The effect on visits of a county population's age structure can change across reservoirs. Some sites may be popular with families, and thus a high proportion of children would have a positive influence on visitation. Other sites may be popular with populations using recreational vehicles. This group tends to be older.

In general, INCOME should have a positive affect on visitation. However, INCOME could have a negative effect if the site in question is a low-cost substitute for higher quality recreation opportunities. Reduced demand in the form of higher incomes was expected with the Sacramento District reservoirs, because other recreation possibilities, such as the Sierra Nevadas, various commercial theme parks, the Pacific Ocean, and several national parks are popular among high income California households.

Installed site facilities

USACE projects are typically complemented by large investments in installed site facilities. Each of the site facility variables at USACE projects is expected to have a positive influence on visitation. Where facilities are excessive compared to demand, additional quantities would have a small or no effect on added visitation. Information on facilities at each reservoir is available from the USACE NRMS database. Totals for facility numbers were collected for day-use picnic tables (PICNIC), boat launch lanes (LANES), total parking spaces (PARKING), camp sites (CAMPS), swimming beaches (BEACHES), full-service marinas (MARINAS), and recreation pool surface acres of the reservoir (SUR_ACRES). Another variable was privately owned boat docks on the site (DOCKS), which may allow more lake access to some

visitors, but private development along a lakeshore may detract from the recreation experience for others. The net effect can only be estimated by examining the visitation data.

Estimating coefficients on the separate effect on visitation of each of these variables is a central objective of this study because these coefficients are used to estimate benefits gained from installing more, or lost benefits incurred from their depreciation or loss. However, collinearity between these facility variables is typically high because they are often designed in approximately constant proportions to vary with the size of the project. A full description of how these variables are analyzed statistically is presented in Chapter 4. Next, attention is turned to site variables other than installed site facilities.

Fishing quality

Visitation is generally expected to increase with improvements in fishing quality. Because reliable fish catch data from sources such as creel surveys is not available for the study projects, several proxy variables were formulated. The first is the number of game fish species available in the reservoir (SPECIES). This variable was obtained from individual USACE site brochures widely available to the public and by contacting recreation managers at each project. Still, some fish species, such as bass and trout, are more desirable than others. Therefore, a separate variable was defined for each of these species. The variable TROUT was equal to 1 if trout were present in the reservoir and equal to 0 if none were present. The variable BASS was similarly defined.

Another fishing quality variable is the number of catchable-size fish available in a given period from previous stocking at the reservoir. Information on annual fish stocking was available from the conservation (fish and game) agencies of California, Missouri, Kentucky, Arkansas, and Tennessee. The variable STOCKING was defined as the total number of catchable-size stocked fish in the reservoir during year k resulting from stocking in the current or previous years. Because stocked fish vary in size, the number of fish stocked in a given year does not necessarily represent the number of catchable fish. Therefore, breaking down the yearly fish stocking data is required to accurately reflect the number of stocked fish that survive to adult, catchable fish in future years.

Fish stocking data are available in several size categories, including catchable, subcatchable, fingerlings, yearlings, and fry. Only catchable fish are included, since subcatchable fish are not expected to add significantly to the fishing experience. However, some smaller fish eventually grow to become catchable fish in future years. Thus, information is needed on the number of smaller fish that survive to maturity by way of the dynamics of fish growth and survival.

Fish survival rates in California were obtained by contacting Almo Cordone, a biologist with the California Department of Fish and Game. Subcatchables and fingerlings are of sufficient catch size the year after stocking. Cordone states that most fish of catchable size do not carry over into the next year. His estimates of survival rates are based on personal experience. More general trends are available in "Inland Fisheries Management" by Calhoun (1966), who summarizes several studies on survival rates. Fingerling survival in California after 1 year is about 20 percent. Some fingerlings may still be present after 2 years, about 5 percent. Survival rates are slightly higher for subcatchables, about 25 percent after 1 year and 10 percent after 2 years. The formula used to estimate the number of catchable fish for Sacramento District reservoirs in year *k*, is

$$
\begin{aligned}
STOCKING_k = {} & CATCHABLES_K + (0.20 * FINGERLINGS_{k-1}) \\
& + (0.05 * FINGERLINGS_{k-2}) \\
& + (0.25 * SUBCATCHABLES_{k-1}) \\
& + (0.10 * SUBCATCHABLES_{K-2})
\end{aligned}
\tag{24}
$$

Implementing this formula requires data on fish stocking of previous years. Therefore, we obtained 1981 through 1985 fish stocking data to approximate the number of remaining catchable-size stocked fish in each Sacramento District reservoir from 1983 through 1985.

For survival rates for the other two USACE districts, Mike Armstrong of the Arkansas Fish and Game was contacted. Stocking data include the fish sizes of catchable, yearling, fingerling, and fry. Little data on survival rates are available, but Armstrong produced estimates. For yearlings, a 25-percent survival rate is used for the second year with a 10-percent carryover into the third year. For fingerlings, 10 percent are estimated to reach catchable size in the second year. For fry, only 3 percent reach catchable size in the third year. The formula applied to the Little Rock and Nashville districts for determining catchable fish in year *k* is

$$
\begin{aligned}
STOCKING_k = {} & CATCHABLES_K + (0.10 * FINGERLINGS_{k-1}) \\
& + (0.25 * YEARLINGS_{k-1}) \\
& + (0.10 * YEARLINGS_{K-2}) + (0.03 * FRY_{k-2})
\end{aligned}
\tag{25}
$$

Use of the fishing quality variables described above has limitations. None of the variables adequately expresses the overall fishing quality at a lake. For example, fish stocking may be necessary to offset poor fishing in naturally unproductive lakes, especially those close to population centers. The number

of fish species also may not reflect fishing quality. Thus, a search was made for an additional fishing quality variable.

Further investigation of a general fishing quality index was pursued through discussion with fisheries biologists at New Mexico State University and University of California, Davis. Upon their recommendations, we selected the morphoedaphic index (MEI) as an indicator of overall fishing quality. The MEI is defined as total dissolved solids (TDS) divided by the mean depth of a reservoir. MEI is a proxy for overall biological productivity of a reservoir. Mean depth is calculated as storage volume divided by surface area, both of which are in the NRMS dataset. The MEI has been positively related to fish catch rates and standing stock (Jenkins 1982). Mean depth of each USACE reservoir is available from the NRMS dataset. Information on TDS is available from the individual USACE districts.

Water quality

Water quality is an important factor affecting recreation benefits of USACE reservoirs. Unfortunately, water quality data proved difficult to acquire. Initial attempts to collect data through a national water quality database (STORET) proved unsuccessful. Typically, monitoring during the study years (1983 through 1986) was inconsistent, and reliable data could not be obtained for many variables. Because consistent data were not obtainable on many water quality measures, only two variables, water clarity and total dissolved solids, are included in the database of this study.

The impact of water quality on visitation may be a result of visitors' perceptions rather than actual water quality. Steinnes (1992) studied the economic value of effect of several water quality measures on the value of lakeside lots in Minnesota. Lake clarity, as measured by secchi disk readings, had the largest positive influence on land values. Because visitors typically have no access to objective measures of water quality, secchi disk levels of USACE reservoirs are used in the present study to represent visitors' perceptions of water quality.

Data on secchi readings (SECCHI) for the study years were available from water quality managers in each USACE district. The value of SECCHI was the average of all secchi readings taken at site j during year k, measured in feet of depth. Visitation is expected to be positively influenced by SECCHI if visitors prefer reservoirs with high clarity. However, anglers may prefer less clarity if it leads to greater fish production and increased catch rates.

The other water quality variable included in the database is TDS, measured in milligrams per liter. Normally, several TDS readings were available for a reservoir for each year surveyed. TDS is needed to calculate the value of MEI, as previously described in this chapter. Also, TDS has the potential to enter the visit predictor equation as a separate water quality variable.

Water levels and variability

Visitation is expected to increase as the water level at a reservoir rises toward the designed recreation pool. Also, visitation should be greater at reservoirs with a steady water level than those which fluctuate widely. This effect should be most evident in the Sacramento District where some reservoirs fluctuate greatly during a recreation season due to agricultural and municipal demands. These competing demands for water cause water levels to fall toward the end of summer.

Data on water levels at each reservoir were available from recreation managers at each USACE district. All water level variables are based on readings of surface acres because visitors have responded more to surface area than volume or elevation. Monthly average surface acre readings were recorded for all sites during the study years. Using an annual average of these monthly readings to represent water levels obscures the fact that most visitation occurs during the summer months. To correct for summer use, estimates of monthly recreation use at each reservoir were obtained from the NRMS database, and the proportion of visitors by month was used to weight the importance to recreation visitors of water levels in that month. Thus, water levels during the summer months receive the highest weights.

The resulting variable, WEIGHTED_SA, measures the weighted average of monthly recreational surface acres of site *j* during year *k*. This variable is then divided by SUR_ACRES (the designed recreation pool surface acres) to determine whether a reservoir is full for recreation purposes. The value of this variable, PCT_FULL, was calculated using the following formula

$$\begin{aligned} \text{PCT\_FULL} &= (\text{WEIGHTED\_SA}/\text{SUR\_ACRES}) * 100 \\ &\quad \text{if WEIGHTED\_SA} < \text{SUR\_ACRES} \\ \text{PCT\_FULL} &= 100 \text{ if SUR\_ACRES} \geq \text{WEIGHTED\_SA} \end{aligned} \tag{26}$$

Reservoirs with low water levels are hypothesized to have a negative effect on visitation. Water levels above the recreation pool level may also impact visitation. However, preliminary specification of a variable to express water levels above the recreation pool produced poor recreation predictions. Thus, application of model results to flood conditions will produce unreliable results.

An additional indicator of reservoir water level is specified in an attempt to account for lake level fluctuations. Because lake level fluctuations during the winter should have a minimal impact on visitation, winter lake levels are not considered in calculating lake fluctuations. For the Sacramento District, the 3 months with the lowest visitation (November to January) are excluded from the specification of water surface area. For the Little Rock District, the months of December to February are excluded. Because winter in the Nashville District is slightly longer, the 4 months with the lowest visitation are eliminated (November through February).

A common choice for measuring lake level fluctuations is a variance or standard deviation. However, the variance numbers do not standardize for overall lake size. Thus, a given variance in surface area may have a large impact on a small reservoir but a negligible effect on a large reservoir. To calculate a standardized measure, the coefficient of variation (CV) is used for this study. The value of CV is calculated by Mendenhall, Wacherly, and Sheaffer (1990) as

$$CV = \text{standard deviation}/\text{mean} \tag{27}$$

The value of CV uses the standard deviation of nonwinter monthly average surface acres at reservoir j during year k. CV is hypothesized to have a negative effect on visitation in the models.

The final water variable specified was shore miles of the reservoir (SHORE). Holding other factors constant, visitation may vary between circular reservoirs and those with many branches. Branching reservoirs may allow boaters a more secluded experience and could affect fishing quality. On the other hand, circular reservoirs may allow more open space for water sports. The expected effect of the SHORE variable on visitation is therefore ambiguous. Although not done for this study, an index of circularity could also be specified as the ratio for shore miles to area. A smaller ratio would indicate greater circularity.

Travel cost

In economic theory, the basis for the travel cost model is that visitation is expected to decrease as origins become more distant, other factors held constant. Travel distances from county i to site j were calculated using the computer program PCMiler®, which measures road distances and travel times between zip codes or cities.[1] The origin point for visitors in any county was defined as the largest city in the county, determined from census data.

Up to four destination points are chosen for each site, allowing visitors to travel to the nearest major recreation area on the reservoir, some of which are quite large. PCMiler® was used to calculate the one-way travel distance from the largest city in county i to each potential recreation area at site j. Since PCMiler® calculates distance between cities only, the distance between recreation areas and the closest city needed to be estimated for the calculations. Once travel distance to each potential recreation area was calculated, the smallest travel distance was chosen to represent the one-way travel distance from county i to site j (MILES). The associated travel time (TIME) was also computed using PCMiler®, based on most practical routes.

[1] The software is published by ALK Associates in Princeton, NJ.

Both travel distance and travel time are important elements in total travel costs. Failure to include travel time understates estimated recreation benefits (Cesario 1976). Including each as an independent variable typically produces unreliable results, as travel distance and time are highly correlated. Travel costs were defined in this study as the sum of actual travel costs plus travel time costs which accounts for the effects of time. Time is valued at one-third the average per-capita county wage rate given in the 1980 census. This value is recommended by the U.S. Water Resource Council (1983). Also, one-third the wage rate reflects the median of Cesario's (1976) survey on the revealed value of travel time in the transportation literature and has been widely used in subsequent travel cost models (Ward and Loomis 1986). Because no data were available on the distribution of children and adult visitors from the visitor's survey, no separate opportunity cost of time accounting was made for children.

Data on the costs of operating motor vehicles were obtained from the U.S. Department of Transportation (1990). Only variable costs of travel (gas, oil, tires, and maintenance) are considered. Use of variable costs is recommended by the U.S. Water Resources Council (1983). Vehicle costs are converted to 1980 constant dollars as all income and other monetary data are from the 1980 census. Conversion of 1980 dollars to any more recent year can be accomplished by using the inflation factors in Table 3. Using national averages, variable vehicle operations costs in 1980 dollars per mile (VC_MILE) are $0.03 in 1983, $0.06 in 1984, $0.06 in 1985, and $0.04 in 1986.

While all visitors to a project who travel together in the same vehicle expend the same travel time, vehicle costs can be shared. All visitors in a vehicle were specified to share vehicle costs equally. Data were available from the USACE exit surveys on the number of visitors in each vehicle (CAR_LOAD). An average value of CAR_LOAD was calculated for each site.

As a final consideration, each trip involves a fixed cost consisting of some amount of planning, preparation, and loading and unloading. An additional $1.00 was added to travel costs for all observations to account for this fixed cost. This value assumes about 15 minutes of pre-trip preparation and packing and 15 minutes of after-trip unloading. Average per-capita wage rates in the sample are about $6.83/hour. Valuing time at one-third the wage rate would give an opportunity cost of time of about $2.28/hour. Thus, assuming a total of one-half hour for pre- and posttrip activities, adding $1.00 to travel costs appears appropriate. The additional $1 for all visitors is not a trivial change in the travel cost variable for the log-log model used to specify this study's demand model. The added $1 cost varies by a different proportion for each origin. It also eliminates extremely high prediction from nearby zones of origin that would otherwise result from the log model. The log-log specification is discussed in more detail in Chapter 4.

The final calculation of total travel costs is

$$TOT\_COSTS_{ijk} = 2 * [[(VC\_MILE_K * MILES_{ij}) / CAR\_LOAD_j] + [TIME_{ij} * (WAGES_i / 2{,}000) * 1/3]] + 1 \tag{28}$$

Recreational substitutes

Potential visitors to USACE reservoirs have many other recreation opportunities that may substitute for USACE reservoirs. Substitutes for this study are based on a similar water-based recreation opportunity. Access to free-flowing rivers was not considered a sufficiently close substitute. Data were collected on the location of all lakes and reservoirs within 250 miles of each county in the database as well as the recreational surface acres of each substitute site.

A substitute site is assumed to be more attractive to visitors the closer it is to their origin and the larger it is. A substitute index approach similar in spirit to Knetsch, Brown, and Hansen (1976) was adopted. For the i^{th} county of visitor origin, the substitute variable was measured as total distance-deflated surface acres of water-based recreation accessible to that county's visitors. It is equal to

$$SUB_i = \sum_k \frac{SUR\_ACRES_k}{MILES_{ik}} \tag{29}$$

where

$k = k^{th}$ substitute water body facing visitors from the i^{th} county

Thus, consistent with economic theory, counties with larger, closer, or more substitute water are expected to send fewer visits to USACE projects. The substitute measure in Equation 29 does not account for the proximity of many counties to ocean-based recreation sites. Visitors interested in swimming may consider the ocean a valid substitute. Visitation to a Great Lake also may be a close substitute for those in some counties who visit project reservoirs in and around the Nashville District. For these reasons, an additional variable was defined as the one-way travel distance from county i to the nearest ocean or Great Lake recreation site (OCEAN). Counties near ocean recreation sites should have lower visitation rates to USACE reservoirs, other factors being equal.

Summary

Table 4 gives a complete list of independent variables assembled for this study's database. The most important variables, such as population, travel costs, facility levels, and substitutes are included in all travel cost models. Other variables are included depending upon their contribution to the model. The next section details how these and other issues were resolved in estimating the models. The flowchart in Figure 1 illustrates the organization and structure of the complete dataset.

Database Results

Several descriptive statistics are presented to illustrate the similarities and differences among the three USACE districts. Table 5 presents mean values for all independent variables. Several differences among districts are apparent. Because counties in the Sacramento District tend to be large, the average population of these counties is about 10 times that of counties in the Little Rock and Nashville Districts. For other demographic variables, counties in the Sacramento District tend to have higher income levels, higher percentage of Hispanics, and fewer people over age 65 than the other two districts. Overall, the Little Rock and Nashville Districts have similar demographic characteristics.

USACE projects in the Sacramento District tend to be smaller with fewer facilities. There are no private docks located on any of the Sacramento District sites. Sacramento District sites tend to have lower water levels and more relative variability in water levels than the Little Rock and Nashville Districts. Also, lake visitors in the Sacramento District have fewer total water-based substitute recreation opportunities. The Little Rock District sites are the closest to having full water levels, but the Nashville District sites have the lowest relative lake level. Nashville District sites are stocked with the least game fish. All sites in all districts contain bass, but not all have trout.

4 Model Estimation

Modeling work began after data were organized into a complete dataset. Prior to modeling, it was necessary to be sure that the data collected for the model was complete and accurate. In December 1992, the complete dataset was sent to WES for inspection. Several missing values, miss-coded data, and other anomalies were uncovered and adjusted.

This section describes the methods of analysis used to specify and estimate the RRDM's. Also described are the computation of economic benefits, benefits per visit, and incremental benefits from facility improvements. A total of eight regional travel cost models are estimated for this study. Day-use and camping models are estimated for each of the three individual districts for a total of six models. Day-use and camper models are also estimated on a pooled dataset of all three districts, for a total of eight models.

Economic Concepts Underlying Travel Cost Models

Consumer surplus

Some visitors to USACE projects would be willing to pay much more than the existing entry fee, while others would not. The maximum amount one is willing to pay for any resource depends on income, price, and quality of available substitutes and intensity of preferences for the resource. Consumer surplus is the difference between the maximum amount someone will pay for a resource and the actual price paid. Consumer surplus is always nonnegative.

A demand curve is the relationship between the price of a resource and the quantity demanded. Generally, as the price of product increases, less is demanded. At any given price, only those who are willing to pay at least the purchase price will demand the resource. A higher price reduces the number of buyers for whom willingness to pay exceeds price. Aggregate consumer surplus over all USACE project visitors is computed as the sum of each individual visitor's consumer surplus. As the price per visitor is increased through entry fees or higher costs of travel, individual and aggregate consumer surplus decreases.

The concept of consumer surplus as an economic benefit applies to a resource such as reservoir recreation. Travel cost analysis permits estimation of a demand curve for a recreation site. Even though all visitors to a site pay a similar entry fee (which may be zero), the travel cost from different zones-of-origins will differ. Visitors from distant origins pay a higher travel cost than those from nearby. The concept can be explained with an example.

Consider two geographical zones located different distances from a recreation site. One origin zone (Zone A) is near the site while the other (Zone B) is more remote. Visitors from Zone A face a lower price to visit the site because their travel costs per trip is lower. The difference between the average travel costs for a visitor from Zone B and the costs for a visitor from Zone A is measurable. Also, the visitation rates for the two zones can be estimated. Because visitors from nearby face a lower cost, they will visit at a higher rate, all other things being equal. Suppose the price per visit to the recreation site rises because of an increase in entrance fees. Assume the cost increase is equal to the per-visit price difference between travel from the two zones. Visitors from Zone A are now faced with the same costs for a visit which previously existed for those in Zone B and should visit at the same rate as was observed previously from Zone B. An important assumption of travel cost analysis is that visitors from Zone A will now visit the site at a rate equal to that which previously existed for Zone B, all other things being equal.

The range of travel costs from different origin zones allows estimation of a full demand curve. An illustration of the demand and consumer surplus for a recreation site is given in Figure 2. One knows that at the existing costs

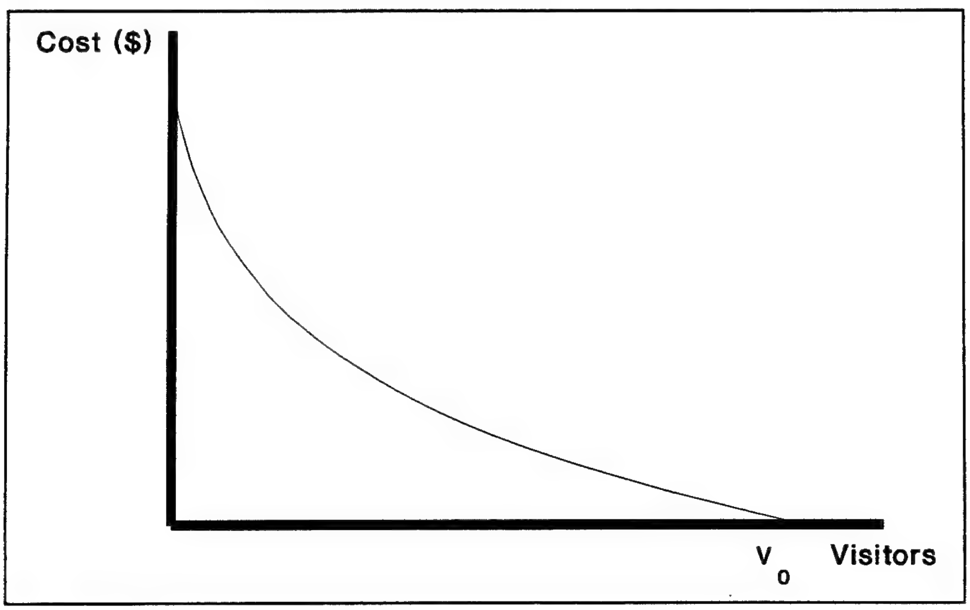

Figure 2. Recreation demand and consumer surplus

(travel costs plus entrance fees), aggregate visitation is V_0. The horizonal axis of Figure 2 represents existing costs. These costs are not necessarily zero, although they are illustrated as zero for simplicity. The relationship between visitation rates and the travel costs of different zones, as well as other important variables, is statistically estimated when fitting a TCM. The impact of increases in the price of a visit can then be predicted. Figure 2 illustrates a representative recreation demand curve. As the price of a visit increases, the number of visitors decrease. The area under the demand curve is the total consumer surplus associated with the recreation site.

Economic effect of entry fees

Figure 3 demonstrates the impact of an increase in entrance fees on total recreation benefit. Assume initial fees are zero and visitation is V_0. The initial consumer surplus is area (A + B + C). Next, suppose an entrance fee of F per visitor is initiated. The intersection of the fee level F with the demand curve results in visitation falling from V_0 to V_1. The modified consumer surplus, area A, is the area under the demand curve but above the entry fee F. The lost consumer surplus is area (B + C). That is, the free benefits previously received by visitors has fallen by area (B + C). However, some fee revenue is now collected at the recreation site. The amount of fee revenue in area B is also equal to the fee of F multiplied by the new visitation level of V_1. The fee revenue gained offsets some of the loss in consumer surplus. The net economic consequence of the entrance fee is shown as the loss of area C. This loss is referred to as the deadweight loss of a price increase.

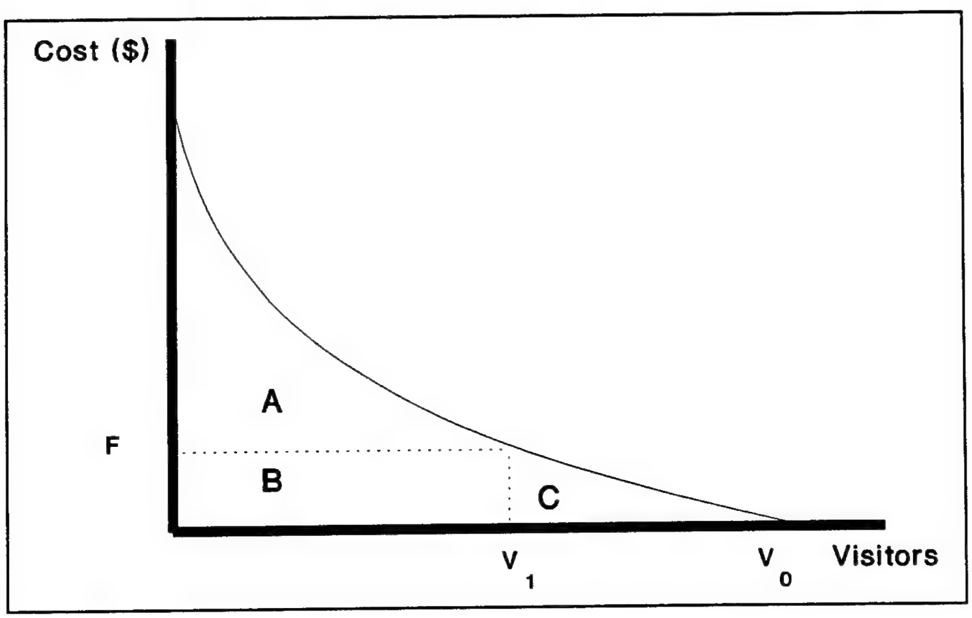

Figure 3. Economic effect of a change in site entry fees

Economic effect of resource quality changes

Another resource management application is a change in resource quality. This is illustrated in Figure 4. Suppose that the outer demand curve is associated with a high initial quality for some site attribute, such as water level at full pool. The initial consumer surplus is area A + B. A reduction in site quality shifts the visitation demand curve to the left. A reduction in site quality could be caused by low water levels due to drought or drawdowns, which render some facilities difficult or impossible to use. In Figure 4, the visitation level at the lower quality level is V_1, and the consumer surplus is area A. The change in consumer surplus from the reduced quality is the area between the outer and inner demand function area B.

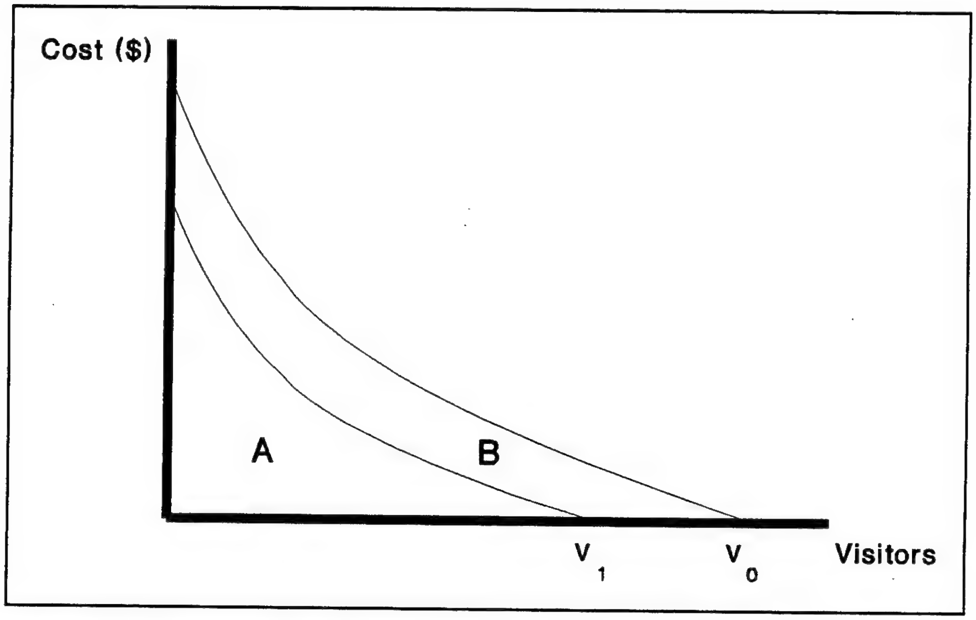

Figure 4. Economic effect of a change in resource quality

Elasticity of demand

Price elasticity of demand is defined as the percentage change in the quantity demanded brought about by a percentage change in price. For most goods and services, such as outdoor recreation, price and quantity demanded (visitation) are inversely related, therefore, elasticity is negative. An increase in price will lead to a decrease in visits, and a decrease in price will lead to an increase in visits. To ease in analysis, the RRDM defines elasticity as the absolute value of the quantity: percent change in visitation/percent change in price.

$$\text{ELASTICITY} = |(\Delta\text{visits} / \text{visits}) / (\Delta\text{price} / \text{price})| \tag{30}$$

If outdoor recreation has an elasticity of 1 (unit elasticity), a 1-percent increase in price will lead to a 1-percent decrease in visits; conversely, a 1-percent decrease in price will lead to a 1-percent increase in visits. If elasticity is greater than 1, a 1-percent change in price will lead to a greater than 1-percent change in visits. If elasticity is less than 1, a 1-percent change in price will lead to less than a 1-percent change in visits. Resources with elasticities greater than 1 are referred to as elastic, while resources with elasticities less than 1 are referred to as inelastic.

Figure 5 illustrates the concept of price elasticity. The demand curve for two different recreation areas are presented side-by-side. At the initial price level P_0, the quantity demanded for the recreation area on the left is V_0 and the quantity demanded for the area on the right is V_0'. Suppose price is increased to P_1 for both areas because of higher gasoline prices or because of increased entry fees. For the steeply sloping demand curve for the area on the left, the quantity demanded decreases only slightly to V_1 possibly because the area has several unique onsite resources or is located in a desirable area. For the flatter demand curve for the area on the right, the quantity demanded decreases significantly to V_1'. The recreation demand curve on the right is said to be more price elastic than the demand curve on the left. Typically, recreation demand curves are more price elastic for sites located where there are numerous substitutes or where available substitutes are perceived by visitors as having better quality, more diversity, or more extensive facilities.

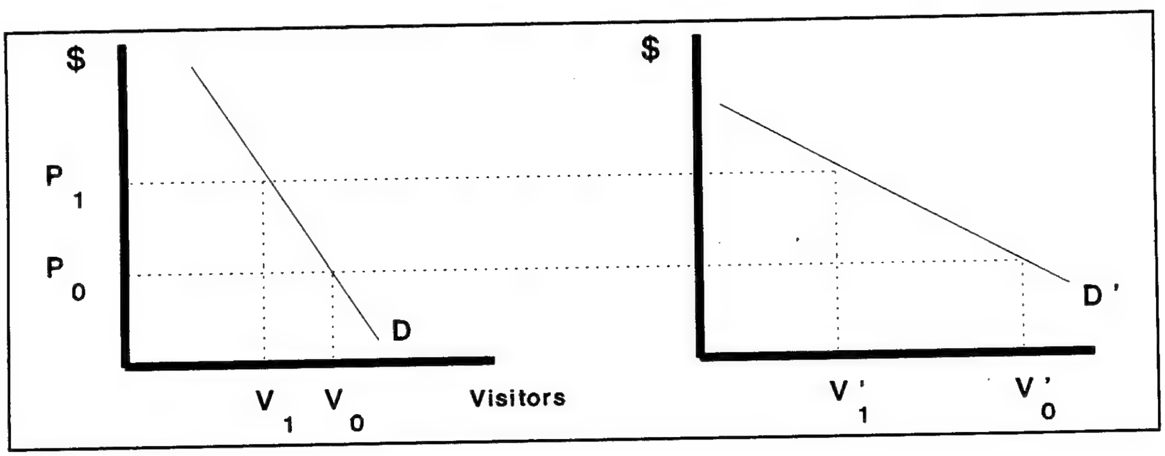

Figure 5. Elasticity of demand

Figure 6 uses an example from the RRDM estimated for this study to illustrate the concept of price elasticity of demand. The two curves illustrate the contrast in camping demand between Lake Mendocino in the Sacramento District and J. Percy Priest (JPP) Lake in the Nashville District. The estimated price elasticity of the Sacramento District camping model (-2.334) is more elastic than that of the Nashville camping model (-0.743). This means campers in the Sacramento District are more sensitive to an increase in price; visitation decreases more in response to the same increase in price. The likely reason is better quality substitutes for USACE facilities in the Sacramento

District compared to the Nashville District. Actual 1991 camping visitation at these projects was close. Visitation at Lake Mendocino was about 208,000, while it was 268,000 at J. Percy Priest Lake.

The elasticity, the change in visitation resulting from an increase in price, is dependent on the point of the demand curve from which one is beginning. Visitation may be more responsive to a price increase when the original price is low (slope is flatter) than for the same price increase when the original price is higher. That is the demand curve may be more like the JPP curve of Figure 6 rather than the linear relationships shown in Figure 5.

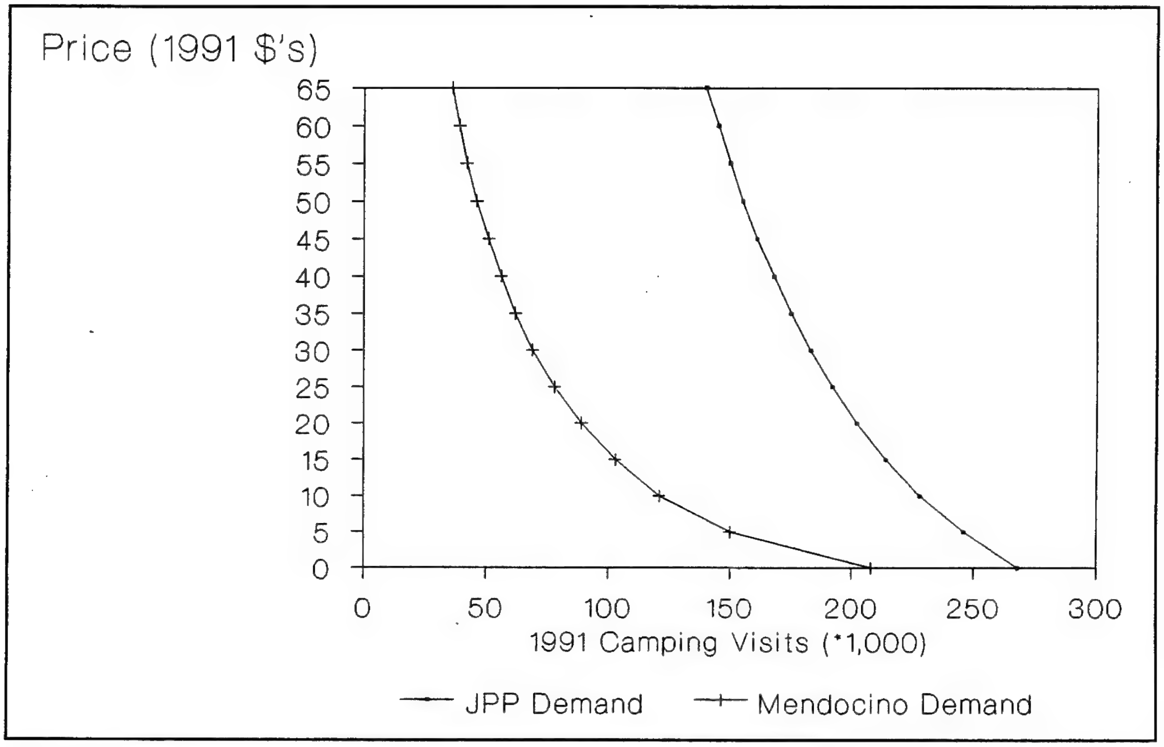

Figure 6. Elasticity example: Camping demand

Figure 6 shows that the demand curve for J. Percy Priest is steeper, or less price elastic, showing less sensitivity to increases in price. This is most pronounced for small changes in price. A small price increase at Lake Mendocino is predicted to decrease visitation much more than a similar increase at J. Percy Priest Lake. The higher price elasticity at Mendocino means that the consumer surplus for camping visitors at Lake Mendocino is low. A small price increase would cause these individuals to discontinue visiting the site. On the other hand, the typical visitor at J. Percy Priest obtains large consumer surpluses. A price increase at J. Percy Priest, while it would decrease their benefits, would have a much smaller effect on total visitation.

Theoretical Background to Model Development

Clawson (1959) originally developed the travel cost method (TCM) for valuing recreation to estimate recreation benefits. Clawson's method is based on the principle that travel cost can be used as a proxy for price in deriving a demand schedule for a recreation site. A zonal TCM is one in which visitors are classified according to their zone of origin; counties are common zones of origin. In an individual TCM, visitors are not classified according to their distance zone. The first step of a zonal TCM analysis involves dividing the market area around the site into zones of visitor origin. Zones are commonly specified as counties because visitor demographic data are widely published at the county level.

The costs from a particular zone to a recreation site are taken to be the same for all individuals in that zone. Based on origin data, a visitation rate is calculated for each zone. Regression analysis is used to estimate a mathematical function for visitation rates at the site as visit rates change with travel cost and demographic data across zones of origin.

The different travel costs for making a trip from each of several origin counties surrounding a site are plotted against the number of trips per capita from each county to the site. These different combinations of travel cost and trips per capita represent price-quantity points that trace a demand curve. From this demand curve, the consumer surplus or net willingness to pay for recreation at a particular site can be calculated. For any given zone of visitor origin, the consumer surplus is calculated as the area under the demand curve that lies above the travel cost. It can be thought of as the travel cost savings of visitors from a given zone of origin compared to visitors who originate from the edge of a project's market area.

Consumer surplus sometimes stands as a conceptual stumbling block for analysts who conduct economic resource valuations. Consumer surplus may be difficult to see as an economic measure of benefit because it represents expenditure not actually collected by a business or government agency. However, estimates of consumer surplus can be verified in cases where visitors are charged a price equal to their maximum willingness to pay for each unit. Such pricing schemes exist. However, governments often do not implement such pricing practices so as to capture the full willingness to pay for each unit as actual revenue, including consumer surplus.

The TCM requires data on visitor travel cost to a recreation site. If surveys providing distance and city or county of residence are available, they should be used. However, one advantage of the TCM is that existing information from boat license records, hunting licenses, game tags, or even license plates can be used to determine the visitor's residence. If one knows the visitor's residence, round-trip distance to the site can be calculated from maps or using commercially available software packages. Distance can be converted to a travel cost by using the publication, "Cost of Owning and

Operating a Motor Vehicle" (U.S. Department of Transportation 1990 or more recent years).

Information on visits must be grouped by county so the visitation information can be merged with county population and other demographic variables that take different values for different counties. Number of trips or visits is the dependent variable in the regression analysis used to estimate the demand curve statistically. For this reason, it is generally important to know visitors' county, city, or zip code. The number of recreationists per vehicle is also useful in computing average travel cost.

The demand equation estimated by the TCM does considerably more than simply relate price to quantity of visits. As described in Chapter 2, several visitor characteristics that influence visitation, such as income or education, vary in addition to price. Moreover, site facilities typically exert a significant influence on demand.

In addition to calculating recreation benefits, the site demand curve can be used to predict recreation use. The travel cost demand equation can be used to predict visitation at a new recreation site or to estimate how visitation at an existing site will change if one of a number of factors changes. These factors include the characteristics of the site, the admission fee, population surrounding the site, access to substitute sites, or any combination of factors. When predicted visitation is plotted against added travel costs, these added costs represent a hypothetical admission fee or added cost. The resulting graph is known as the second stage demand curve (Dwyer, Kelley, and Bowes 1977). The use of the general equation to estimate total visitor use can contribute information toward designing a facility to meet the needs of people in a particular market area.

Regarding the TCM, there are two important categories of assumptions; the first category ensures that the use of travel costs as a proxy for price is correct, while the second category addresses assumptions necessary to estimate the demand curve statistically. If these assumptions are grossly violated, the method is inappropriate and should not be used.

The key assumption necessary to interpret travel cost and travel time as a price of recreation is that key variable costs that affect trip-making behavior can be measured correctly. For this study, variable costs are the costs that vary with distance.

Assigning variable costs to trip-making behavior is easiest when three conditions hold:

a. Travel is incurred exclusively for visiting a site under study.

b. There are no benefits from the travel itself, so that travel costs and travel time represent the price paid to visit the recreation site.

c. The opportunity cost of travel time can be estimated.

If visitors make a trip for many purposes, travel costs are entangled in the joint production of several goods or services. It may not be possible to assign a portion of the trip costs to a specific purpose. For example, assume a visitor takes a trip to see friends and enjoy visit a recreation site. The usual solution is to discard the multiple purpose observation when estimating the benefits of the recreation site. A more sophisticated approach is to estimate the incremental cost incurred by a multiple purpose to the site visitor in question (Haspell and Johnson 1982).

It is commonly assumed that there are no benefits gained or lost from travel itself. If this assumption is violated, travel cost and travel time fail to represent the cost of visiting the recreation site. How to adjust travel cost estimates if this assumption is untrue is partly related to the issue of the opportunity cost of travel time.

For many years, one of the most challenging issues regarding the TCM has been how to value travel time. The value assigned to travel time can markedly affect the benefit estimates derived from TCM. Many authors have discussed issues related to selecting a value for the opportunity cost of travel time (Cesario and Knetsch 1976, Cesario 1976, Wilman 1980, McConnell and Strand 1982). Empirical work reviewed by Cesario (1976) suggests that the opportunity cost of travel time lies between one-fourth and one-half of the wage rate. Whatever value is assigned to travel time, it must account for any added benefit or cost of travel itself, as well as the value of time visitors forego in its best alternative use.

When the visitor travels, the time it takes to travel to the site is a cost of producing recreational trips. Other things the same, less cost is preferred to more. Therefore, time costs are added to vehicle operating costs when calculating the price a visitor must pay to visit the site. Assumptions necessary to statistically estimate a travel cost demand function are the same as those required to estimate any other demand function.

The first assumption is that there must be sufficient variation in prices (travel cost) to identify the demand function statistically. This means that recreationists must come from enough different areas of origin to provide a range of distances by which to trace out the demand curve statistically. Violating this assumption precludes statistical estimation, and therefore the TCM cannot be applied.

Second, all significant variables that affect demand are included in the TCM model and the functional form is correct. While the number of

variables that influence recreation behavior is large, typically only a small number contribute significantly for statistical purposes. In addition to travel costs, variables such as income, availability of substitute sites, and attractiveness of the site are among variables that are consistently significant or theoretically important. To further simplify the task, only variables that vary from person to person (or origin to origin in the aggregate model) need to be included. In the TCM, for example, the presence of golfing opportunities might influence visitation to a recreation site. However, if all zones are assumed to have equal golfing opportunities, this factor can be omitted from the TCM.

The third requirement for a TCM to be valid is that there is no shortage of the recreation resource in question resulting in unsatisfied demand. If, at a given price, there is more demand than supply, some of the demand will be unobserved. For recreation sites, this means that there must be enough capacity to satisfy demand. A strategy for implementing TCM when there are capacity restrictions has been outlined by Loomis (1982).

Model Specification

Many algebraic functional forms for equations that predict recreational visits have been used for zonal travel cost models. The definition of the dependent variable may suggest certain functional forms. For example, a dependent variable with a significant number of zero observations may be modelled using Tobit or Heckman sample selection models (Bockstael et al. 1990). As discussed in Chapter 3, this study considers 0 sampled visits to be a small sample problem rather than an indication of 0 population visits.

Functional forms

Zero population visits are possible if the dependent variable is calculated using the formula

$$TOTAL\_VIS_{ijk} = SAMPLED\_VIS_{ijk} * SIMPL\_EXP_{jk} \tag{31}$$

This is discussed at length in Chapter 3.

Several demand model specifications used in previous travel cost demand studies were considered for estimation in this study. Three model performance standards were used. First, a demand model should predict nonnegative visitation for any site under any conditions of project operation. Next, total benefits should increase at a decreasing rate with any project facility improvements. Finally, average benefits per-visitor day should be constant or increase with improvements in project quality.

Using these three performance criteria, the following four models were brought forth for further consideration.

$$\text{Simple linear } V = \beta_0 + \beta_1 \text{ Price} + \beta_2 \text{ Facilities} + \beta_3 \text{ Demographics} \tag{32}$$

$$\text{Log linear } V = \beta_0 \text{ Price}^{\beta_1} \text{ Facilities}^{\beta_2} \text{ Demographics}^{\beta_3} \tag{33}$$

$$\text{Semilog \#1 } V = \beta_0 + \beta_1 \ln(\text{Price}) + \beta_2 \ln(\text{Facil}) + \beta_3 \ln(\text{Demographics}) \tag{34}$$

$$\text{Semilog \#2 } \ln(V) = \beta_0 + \beta_1 \text{ Price} + \beta_2 \text{ Facilities} + \beta_3 \text{ Demographics} \tag{35}$$

where

V = visits

Price = travel cost including travel time and entry fees

Facilities = a list of several variables that vary by site, including water, fishing, and the like

Demographics = variables that vary by zone of origin

"ln" = the natural log of the subsequent variable

The linear model was rejected for this study because it predicts negative visits when a project has sufficiently few facilities or price is sufficiently high. Both semilogs #1 and #2 were also rejected because they fail to consistently allow for decreasing incremental benefits in the face of increasing site quality.

The log linear model described by Equation 33 was brought forth for estimation because it met all three criteria: never predicted nonnegative visitation, decreasing incremental benefits with site improvements for values of the parameters in a relevant range, and constant average benefits per visit with site improvements. None of the remaining three models passed all three tests described above. Moreover, the β coefficients in the log linear model (Equation 33) are identical to elasticities. For example, in Equation 33, if β_2 is estimated to be 0.5, then the facility elasticity is 0.5. That is, a 1-percent change in the quantity of facilities increases visitation by 0.5 times 1 percent, or 0.5 percent. The remaining coefficients in Equation 33 have a similar elasticity interpretation.

In addition to the functional form described, preliminary experimental model runs were tried for a nonlinear least squares model and a Heckman sample selection model for the purpose of testing transferability of models among districts. Additional details are in Loomis et al. (1995).

Market area selection

Market areas are determined for the models to include all sampled visitors within the market area and exclude those outside the area. The USACE exit surveys did not ask respondents whether their visit was part of a multidestination trip. However, for visitors who originate from distant counties, the USACE project is more likely to be one of many destinations. As the analysis includes greater market distances, more multidestination travelers will be incorrectly included.

Multidestination visitors from longer distances typically exhibit different travel behavior than nearby visitors, which is reflected in decreased explanatory power of regression models as the market area is increased beyond a threshold distance. Because distant travelers are more likely to be multidestination visitors, a limited market area is needed. Another factor favoring a small market area is that more distant counties are likely to produce a higher percentage of counties with no sampled visitors. Including too many counties without visits reduces the variability of the dependent variable. On the other hand, a model should capture the majority of visitors to a site where possible. Otherwise, models cannot accurately predict total visitation and benefit changes resulting from management actions. This criterion favors a large market area.

Another factor that favors a large market area is that the number of observations included in the regression models should be large. Thus, the selection of the best threshold for the market area comes down to the question of including few multidestination trips while including the majority of visitors. The final choice of market area requires a compromise between these conflicting criteria.

Because there is interest in conducting transferability tests for each district's model to the other two districts, market areas should be equivalent across districts. Otherwise, one would expect poor performance in testing transferability among models simply because they had different market areas. Such transfers are expected to fail merely due to a different choice of market area rather than underlying differences in recreation behavior. For example, testing transferability between a Nashville day-use model with a 100-mile market area and a Little Rock day-use model with a 150-mile market area is expected to produce poor results. However, different market areas may be chosen for the day-use and camping models, since the two types of models will not be compared statistically.

To determine the appropriate market areas, the percentage of total sample visitors captured by different market area was calculated. Each market area is one-way road distance as determined by the computer program PCMiler®. The data were sorted into 25-mile market area segments starting at 100 miles and extending to 250 miles. Table 6 shows the number of visitors originating from different one-way road distances. In general, campers tend to travel greater distances than day-use visitors. A 100-mile market area for day users would capture 80 percent of all sampled visitors. For the campers, a relatively large percentage originates in the 150- to 175-mile category. A camper market area of 175 miles includes about 73 percent of sampled campers.

Table 7 illustrates how the number of sampled observations over all sampled years in the given USACE district changes as the market area changes. The Nashville District has a large sample size because surveys were conducted in multiple years. However, the Little Rock and Sacramento Districts have relatively small sample sizes, as the market area is reduced. Increasing the market area from 100 to 125 miles in the Little Rock District increases the sample size by 61 percent. The same change in the Sacramento District increases the sample size by 54 percent. Because the sample sizes are relatively low for the 100-mile market area in these two districts, a minimum 125-mile day-use market area was selected.

Per-capita visitation decreases as travel distance increases, so the percentage of counties with 0 sampled visits is expected to increase with a larger market area. Table 8 shows how the percentage of counties with 0 sampled visits changes with changes in the market area. Tabled values represent averages across the three districts; averages were selected to permit use of a single market area for all districts. Because each project generally has fewer campers than day users, more sampled 0's are observed for the camping data. Because a low percentage of sampled 0's is preferred to more 0's, the numbers in Table 8 suggest using small market areas.

An important issue is how recreation behavior varies across market areas. The explanatory power of the model decreases as the market area is increased if the added visitors differ from visitors in the base market area. If the explanatory power of the model does not drop off with increases in the market area, then a large market area is valid. A dataset was created for various market areas using 25-mile increments, then a double-log ordinary least squares regression was run with estimated annual visits as the dependent variable and the following independent variables: population, CV, per-capita income, reservoir percent full, travel costs, and MEI. The surface acreage of the reservoir was included in the day-use model, and the number of camping sites was included in the camping model. These basic models typically approximate results of a full model with more variables.

The percent of variance explained by the model (R-square) was recorded for each market area and each district and then averaged across the districts. Results are given in Table 9. R-square decreases as the market area increases. These results, similar to those in Table 8, support a small market

area. The final criterion to consider in choosing a market area is that one prefers a small probability of including multidestination travelers. This criterion favors a relatively small market area.

Based on all factors, a 125-mile market area was chosen for the day-use models. This market area includes over 80 percent of sampled visitors, has about 41 percent sample 0's, and the average R-square is above 0.60.

A larger market area is chosen for the camping model for the purpose of including a larger percentage of camping visitors, since a 125-mile camping market area only captures about 60 percent of sampled visitation. Using such a model to predict total visitation changes with management actions may produce misleading results. Also, camping visitors are expected to be willing to travel greater distances than day users. A 175-mile camping market area includes over 73 percent of sampled visitation. Thus, all day-use models will consider a 125-mile market area and camping models include a 175-mile market area.

Ideally, the model would explain recreation behavior accurately for a high percentage of visitors. However, in reality the model presents a tradeoff, either predicting accurately for a low percent of visitors or predicting poorly for a large number of visitors. Tables 7 through 9 illustrate the tradeoff between model accuracy and percentage of visitors accounted for. The compromise is to predict acceptably well for a reasonably high number of visitors. Our market area selection of 125-miles for day users and 175-miles for campers reflects this compromise. Table 10 presents the proportion of sampled visitors by project within the defined market area.

As mentioned previously, defined market areas exclude some single-destination visitors, while including some on multiple-destination trips. Some estimate of the magnitude of these false exclusions or inclusions will determine whether these errors are significant. Excluding single-destination travelers reduces the precision of the fit model for high-cost visitors. On the other hand, including multidestination travelers biases estimates of total recreation benefit, because the travel cost is not totally incurred to visit the project. Nearby multidestination tourists typically stop for a short time only or stop at other recreation sites to justify the complete trip economically. These two sources of bias may work in opposite directions.

More recent USACE exit surveys were conducted in a separate analysis in the Omaha District in 1993 (U.S. Army Engineer Division, Missouri River 1994). In the Omaha District survey, respondents were asked whether they were on a multidestination trip. These data were analyzed as part of a separate parallel study. These visitor data were aggregated to determine the proportion of single- and multiple-destination travelers within the market areas. Summary results are given in Appendix A. The Omaha District surveys show that the defined market areas include the majority of all single-destination travelers (over 90 percent) but include only about 9 percent of multi-destination tourists. Because the percentage of excluded single-destination

visitors equals the included multidestination visitors, and because the biases are opposite in direction, we conclude that the bias of estimated benefits due to these factors is acceptably small for this study.

Model Estimation

Parameter restrictions

Several data limitations required the use of restrictions placed on the parameters. Two problems in particular were collinearity in the facilities at USACE projects and the need for national data sources to make up for data with insufficient variation for the three study districts.

Facility collinearity

Information on the economic value contributed by USACE projects and project facilities can be useful in budget allocations. These values are also useful for decisions about the timing, location, extent, and nature of facility improvements. Such information can offer insight to budget allocations made by the Congress, state resource conservation agencies, and by the USACE among numerous competing projects and facilities. Because economic values of projects and project facilities are important in determining these budget allocations, this study estimates travel cost demand model coefficients for each of several important facility variables.

Estimating separate coefficients for each facility permits one to isolate the separate effects on visitation and benefits of each type of facility. Unfortunately, separating values of each facility is difficult to do, because these variables tend to be highly correlated among each other. This high correlation occurs because USACE facilities have been developed using similar planning and design standards and because the facilities have been developed in proportion with use predictions, which are closely linked to reservoir size. Ordinary least-squares estimation still produces the best linear unbiased estimators despite high multicollinearity (Greene 1993). The problem with multicollinearity is that inflated variances produce unreliable parameter estimates. Symptoms of high multicollinearity include high standard errors and coefficients with wrong signs or implausible magnitudes.

Econometricians have developed few reliable methods for estimating model parameters precisely in the face of multicollinearity. Each of the widely used remedies has serious and well-known limitations. One common approach is to drop some of the independent variables suspected of causing the problem. However, simply dropping variables falsely ascribes all the variation in visitation to the facilities remaining in the equation, thus biasing the estimated coefficients. Two other common statistical remedies are principal components regression and ridge regression.

The basic multicollinearity problem is described below. Begin by defining a hypothetical visitation predictor

$$Y = f\,(X_1, X_2, \ldots, X_n, Z_1, Z_2, \ldots, Z_m) \tag{36}$$

where

$Y =$ total visitation and each of the X independent variables are not significantly correlated among themselves

The Z variables are largely uncorrelated with each X variable but are significantly correlated with each other. In this study, the Z variables are the facility variables, while the X variables include demographics, travel costs, substitutes, water quality, and fishing quality. Table 11 gives the first-order correlation coefficients between all facility variables using the three-district dataset. All correlations are positive (ranging from 0.22 to 0.86), and all are statistically significant at the 0.01 level.

In estimating Equation 36, parameter estimates of the Z variables are unbiased but significantly affected by multicollinearity. In linear form, the model to be estimated is

$$Y = \beta_0 + \beta_1 X_1 + \ldots + \beta_n X_n + \delta_1 Z_1 + \ldots + \delta_m Z_m + \epsilon \tag{37}$$

The estimates of each δ_i will be affected by multicollinearity. Consider the impact of dropping all of the Z independent variables except one. A model would be estimated such as

$$Y = \beta_0 + \beta_1 X_1 + \ldots + \beta_n X_n + \delta_1 Z_1 + \epsilon \tag{38}$$

where multicollinearity would not be a significant problem according to the assumptions of the model. The weakness of Equation 38 is that an omitted variable problem now exists which biases the parameter estimates. To show the bias of Equation 38, rewrite Equation 37 into the following matrix form

$$Y = X\beta + Z\delta \tag{39}$$

where the matrix X includes all X variables and Z_1. The matrix Z includes the remaining Z variables. If the estimation of Equation 38 could be written as

$$Y = X\beta \tag{40}$$

then the parameter estimates can be expressed as

$$\hat{\beta} = (X'X)^{-1}X'Y \tag{41}$$

To find the expected value of β, substitute for Y from Equation 39

$$E(\hat{\beta}) = (X'X)^{-1}X' \ (X\beta + Z\delta) \tag{42}$$

This simplifies to

$$E(\hat{\beta}) = \beta + (X'X)^{-1}X'Z\delta \tag{43}$$

Because each X variable is assumed to not be significantly correlated with any Z variable, the only reason Equation 43 does not show unbias is that Z_1 is significantly correlated with the other Z variables.

As Table 11 shows, all correlations between the USACE facility variables are positive. Thus, by defining any facility variable as Z_1 in Equation 38, and estimating the corresponding coefficient, the parameter estimate will be biased upward. The advantage of estimating Equation 38 is that multicollinearity has been reduced and the standard error of the parameter estimate on Z_1 is lower than if Equation 30 had been estimated. The optimal situation would minimize both bias and the variance of the coefficient. Because one cannot minimize both quantities at the same time, a tradeoff rule must be defined. The mean square error (MSE) has been used to compare the tradeoff between unbias and low variance. MSE of an estimator β is defined by Mendenhall, Wacherly, and Shaeffer (1990) as

$$MSE_{\beta} = (bias_{\beta})^2 + variance_{\beta} \tag{44}$$

The approach used in this study attempts to develop a facility index that minimizes MSE compared to other estimation techniques. This two-stage index approach uses the information in the dataset to determine the relative weights accorded to each facility variable in constructing the index. The first stage of the approach determines the weights of the index, and the second stage uses the facility index as a new independent variable.

For the rationale behind the index approach, consider the model of Equation 38 where only one facility variable is included. According to the assumptions of the model, the parameter estimate on this one facility variable will be biased upward but have a low variance. If one included each of the m facility variables sequentially in a separate regression with all X variables, a matrix of biased coefficients with low variance would be obtained. These first-stage coefficients are used as the weights in constructing the index. Define the first-stage models as

$$Y = \beta_0 + \beta_1 X_1 + \ldots + \beta_n X_n + \tau_1 Z_1 + \epsilon_1$$

$$Y = \beta_0 + \beta_1 X_1 + \ldots + \beta_n X_n + \tau_2 Z_2 + \epsilon_2$$

$$\cdot \qquad (45)$$

$$\cdot$$

$$\cdot$$

$$Y = \beta_0 + \beta_1 X_1 + \ldots + \beta_n X_n + \tau_m Z_m + \epsilon_m$$

The τ_i's are used as the weights for the facility index. In the linear case presented in Equation 38, the index is calculated as

$$I = \tau_1 Z_1 + \tau_2 Z_2 + \ldots + \tau_m Z_m \qquad (46)$$

For a double-log model, the first stage uses the index calculated as

$$I = (Z_1^{T_1}) * (Z_2^{T_2}) * \ldots * (Z_m^{T_m}) \qquad (47)$$

Because all models presented in this study are in double-log specifications, Equation 47 is used to calculate all facility indices.

Because all estimated τ_i's are biased upward, the second-stage model uses the information contained in the data to adjust these coefficients. Specifically, the second-stage model presents a way to reduce the bias of the estimated τ_i parameters. The second-stage model uses the index as an independent variable along with all X variables. In the linear case, the second-stage model is

$$Y = \beta_0 + \beta_1 X_1 + \ldots + \beta_n X_n + \phi I + \epsilon^* \qquad (48)$$

Using the available data obtains an estimate for the parameter ϕ. This estimate is the adjustment factor to apply to the first-stage facility coefficients from Equation 45, τ_1. The estimated β_i's from Equation 48 are used as the final parameter estimates for all X variables.

The final coefficients for the Z variables for the linear case can be calculated by substituting Equation 46 that defines I into the ϕI expression in Equation 48. The substitution produces

$$\phi I = \phi * (\tau_1 Z_1 + \tau_2 Z_2 + \ldots + \tau_m Z_m) \qquad (49)$$

Multiplying the estimated ϕ obtained by fitting Equation 49 gives the final estimated parameters for each facility variable as

$$
\begin{aligned}
\delta_1 &= \phi * \tau_1 \\
\delta_2 &= \phi * \tau_2 \\
&\ \ \vdots \\
\delta_m &= \phi * \tau_m
\end{aligned}
\tag{50}
$$

That is, the final parameter estimate for each facility variable, δ_i, equals the product of ϕ estimated from Equation 48 multiplied by the first-stage facility parameter estimate, τ_i, obtained by fitting Equation 45. In both the linear and double-log situations, Equation 43 is used to calculate the final coefficients on the facility variables.

The facility index approach attempts to deal with both terms of the MSE expression, Equation 44. The first stage attempts to obtain coefficients with low variances, though they are biased. The second-stage attempts to correct for the bias. Based on this theory, the index approach is expected to produce estimated parameters with low MSE's. The issue is whether the index approach produces lower MSE's than other methods, such as OLS, with all variables or principal components analysis. Unfortunately, MSE's cannot be calculated for the actual data because the true coefficients are unknown and the bias cannot be calculated.

A good way to test the index approach is to use Monte Carlo simulations. A Monte Carlo simulation experiment compared the index approach to several methods, including OLS with all variables, dropping variables, and principal components regression. A detailed description of this simulation along with all results is given in Appendix B. Results of the simulations suggest that both principal components and the facility index appear superior to dropping variables and OLS with all variables included. The facility index approach produces estimates with lower MSE's than principal components in five of the six simulation experiments. Additional discussion of the facility index approach is presented in Appendix B.

Coefficient restrictions

Several coefficients (elasticities) in the regional recreation demand model were entered as restrictions based on independent models estimated from outside data sources. Appendix C and Appendix D describe the details.

Weights

Pooled models contain observations from all three districts. Table 7 shows that each district contains a different number of observations within its defined market area. For the 125-mile market area day-use pooled model, the dataset contains 307 observations from the Little Rock District, 993 from Nashville, and 264 from Sacramento, for a total of 1,564 observations. For the camping model with a 175-mile market area, 2,833 total observations include 616 from Little Rock, 1,755 from Nashville, and 462 from Sacramento. For the day-use pooled model, 63.5 percent of all observations originate from the Nashville District. For the pooled camping model, the proportion is 61.9 percent.

Using unweighted OLS regression for the pooled models would produce results heavily influenced by recreation behavior in the Nashville District. Because the preponderance of observations in the Nashville District is due to multiple survey years and small counties in that district, rather than more intensive recreation behavior in Nashville, such an unweighted model would understate the influence of Little Rock and Sacramento. Therefore, Little Rock and Sacramento need larger weights than Nashville. Also, counties in the Sacramento District tend to be larger in population than those in the other districts. The low number of observations in the Sacramento District is due to large county size.

The weights for the Nashville District were set at 1.0 for both pooled models, since it has the highest number of observations for both datasets. The weights for the other districts were then calculated using the formula

$$\begin{aligned} WEIGHT_{Sac} &= OBSERVATIONS_{Nash} \,/\, OBSERVATIONS_{sac} \\ WEIGHT_{LR} &= OBSERVATIONS_{Nash} \,/\, OBSERVATIONS_{LR} \end{aligned} \tag{51}$$

where

$OBSERVATIONS_i$ = number of observations in each district

For the Little Rock District, the weights are 3.23 for the pooled day-use model and 2.84 for the camping model. The Sacramento District weights are 3.76 for the day-use model and 3.79 for the camping model. These weights are used in a weighted least-squares regression to weigh each observation in the Little Rock and Sacramento models.

Estimation method

All models were estimated as a weighted restricted least-squares linear regression using the REG procedure in the SAS® statistical package. Above weights were applied for reasons discussed in Chapter 4. SAS code was written to save first-stage coefficients for facility variables as discussed in

Chapter 4 and to calculate the facility index. Final regression coefficients were then estimated. In double-log form, all estimated parameters are elasticities. That is, the parameter estimated for a variable is the percentage change in visitation resulting from a 1-percent increase in the value of the independent variable (e.g., picnic tables).

Each of the eight demand models were specified and estimated separately based on accepted behavioral theory and based on variables with statistically significant parameter estimates. Consistent with behavioral differences between day users and overnight visitors, the included facility variables were slightly different for the day-use and camping models. Both models include the variables LANES, BEACHES, MARINAS, and SUR_ACRES, since these facilities can be used by both types of users. The day-use model also includes the variables PICNIC and PARKING, since these facilities are used by day users. The camping model excluded these two variables because both parking spaces and picnic tables are provided at camping sites. The variable CAMPS is thus included in all camping models. The variable DOCKS was included in all models except the Sacramento models, because there are no private boat docks on any of the Sacramento District projects.

All other independent variables were brought forward as candidates in each model. Some variables are included in all models based on economic theory and evidence from travel cost studies described previously. These essential (core) variables are:

a. TOT_COST

b. INCOME

c. SUB_INDEX

d. POPULATION

Other independent variables were nonessential due to lack of supporting theory or previous evidence. Nonessential variables were included in a model if they increased the explanatory power of the model, were statistically significant, and did not cause multicollinearity problems.

Results of Estimated Demand Models

This section presents the results of the eight estimated models: one day-use and one camping model for each of the three districts, plus one day-use and one camping model for the pooled dataset. All day-use models use a 125-mile market area; the camping models use a 175-mile market area. Tables 12 through 15 present the regression results for all eight models. Included are results of overall model performance and statistical significance. The percentage of actual visits explained by the variables in the model (R^2) ranges from 0.35 for the Nashville camping model to 0.67 for the Little Rock

day-use model. For each district, including the pooled model, the R^2 of the day-use models is higher than that of the camping models.

The core variables included in all models performed well. All coefficients are interpreted as elasticities, which is the percentage change in visitation produced by a county resulting from a 1-percent change in that visit predictor. For all models, a higher coefficient means that a percent change in the variable has a larger percent change in visits. As expected, all travel cost coefficients (elasticities) are negative and significantly different from 0. The negative effect of travel costs on visitation are greatest (most elastic) in the Sacramento and smallest in the Nashville District. All elasticity coefficients on population in the camping models are less than 1.0. Thus, it appears that rural residents are more likely to camp at USACE reservoirs. The substitute (SUB_INDEX) variable coefficient estimate is negative in all models and is significant at the 0.01 level in six of the eight models. Similar to the findings of Rosenthal (1987), these findings indicate substitutes are important in explaining visitor behavior. The income variable produced mixed results. The coefficient on INCOME is positive in the Little Rock and Nashville Districts (and mostly significant) but not significantly different from 0 in the Sacramento District models.

Several other variables were statistically significant predictors of visitation in one or more of the eight models. The elasticity coefficient on the percent full of recreation pool level (PCT_FULL) is approximately 1.0 for both Sacramento District models. This means that visitation will drop less rapidly as the reservoir's surface area decreases below the recreation pool due to drawdown from drought or competing water uses. This finding suggests that the economic value of additional surface acres for recreation in percentage terms is highest when the reservoir level is held at the recreation pool. Increases in water variability due to reservoir fluctuations over the recreation season (CV) generally reduce visitation, although the negative elasticities are typically less than 1.0 in absolute terms. These results indicate that visitors are attracted to reservoirs that fluctuate little throughout the recreation season.

All 50 elasticity coefficients for the various facility factors estimated range between the theoretically expected 0 and 1. That is, the models predict that visitation increases for increases in all facility variables included in the model, but at a decreasing rate. Only 3 of these 50 coefficients are higher than 0.50 and only 6 exceed 0.40. Except for the parameter estimates for DOCKS, which tends to be low, most coefficients range between 0.10 and 0.40. For the pooled models, marginal increases in marinas are predicted to produce the largest increase in visitation. All four estimates on the elasticity of visits resulting from increase in camping sites are between 0.21 and 0.28. The elasticity of visits from changes in a reservoir's size ranges from a low of about 0.1 in the Little Rock day-use model to a high of 0.426 in the pooled camping model. The elasticity of the number of picnic tables and beaches tend to be smaller, with elasticities typically less than 0.15.

Site variables for water and fishing quality are important in some models. Fishing quality impacts visitation through the variables MEI and SPECIES. Both produced positive and significant coefficients in several models. The variable STOCKING was not significant in any of the models. This may indicate that stocking programs merely offset over-fished natural fish populations, but it also could indicate that stocking programs are not effective in attracting visitors. In any case, interactions between the effectiveness of stocking programs and natural fish populations requires a biology model and are outside the scope of this study. Water quality variables tended to be unimportant. SECCHI did not enter into any of the models, and TDS entered only in two models.

Demographic variables such as UNEMPLOYMENT, MINORITY, and UNDER_18 are important in some models. The Little Rock day-use models show that visitation increases as UNDER_18 increases, and the Nashville day-use model has visitation decreasing as OVER_65 increases. High levels of unemployment tend to reduce visitation. The same is true for high values of MINORITY in the pooled day-use model.

Finally, two climate variables, COOLING_DD and JULY_HUMIDITY, were included in the pooled models. These variables are estimated from a separate regression and are included with restricted parameters. These variables are explained further in the next chapter, when issues of transferability become important.

5 Management Applications

The ultimate purpose of estimating the RRDM is to predict the consequences on recreational visitation and economic benefits resulting from a range of potential management actions, many of which have not been implemented to date. Access to information provided by this model has the potential to save considerable time and resources when conducting economic appraisals of resource management plans. Access to the data, estimated models, and their application to a wide variety of management actions is available with the software and accompanying user's manual described by Ward and Martin (1994).

Model results are given for predicted visit totals and per-user economic benefits. Incremental benefits from facility improvements are also discussed. Other applications will explore the transferability of the models to unstudied sites and years. Visit predictions are calculated for years outside of the study period. These are compared with actual visits to determine the reliability of the model over time. Next, the model is applied to a project in the Sacramento District not included to estimate the model. The benefits or costs of various management actions are then estimated, such as facility changes or different water management actions. Finally, the application of the model to other districts is examined. Examples of applications are chosen for illustrative purposes that represent management issues facing USACE planners.

Models and Decisionmaking

Use of the estimated models

One major reason to estimate any model is to use for structural analysis, which is an investigation of the underlying relationships that govern the decisionmaking of visitors to USACE reservoirs in order to better explain relevant recreational behavior patterns. For the RRDM, structural analysis involves the quantitative estimation of the interrelationships among the variables that affect the demand for recreation at USACE projects. In addition to estimating the RRDM coefficients, structural analysis is concerned with interpreting of several critical coefficients. For the RRDM, these include

coefficients on travel cost, water quantity at USACE reservoirs, income, facilities, and substitute recreation opportunities. Structural analysis is of considerable importance for managing USACE reservoirs, because the estimated sign and magnitude of the coefficients in the demand model provide insight into the consequences of management actions on recreation demand and benefits. Estimated coefficients also provide an estimate of the effects of factors, such as emerging demographic trends, beyond managers' control.

A second aim of estimating the RRDM is forecasting, which is predicting recreation use and benefits beyond the available sample of data used to fit the model. Forecasts produced by the RRDM are quantitative, explicit, and unambiguous, and therefore verifiable, in that there are conceivable outcomes that would validate or refute the forecast. A specific example is the forecast of additional visitation at Black Butte Reservoir resulting from a 10-percent increase in per-capita income in the market area.

A third reason for building RRDM, and arguably one of its most important for USACE, is evaluating the consequences of management actions. This objective refers to a situation in which a decision maker must select one management action, called a "plan," from a given set of alternative plans. An important example is water resources planning, in which USACE decision makers must select among different investments in project facilities, drought control efforts, and storage and release plans that affect recreational and total national economic benefits in the watershed region. Management action evaluation is closely related to forecasting. In fact, forecasting and management evaluation is characterized by a feedback system. A good forecast of visitation at USACE reservoirs must be based, in part, on assumptions concerning management actions at those reservoirs. Conversely, an ideal evaluation of potential management actions is partly based on forecasts of the effect of variables affecting recreational visitation beyond control of the USACE. Examples include emerging demographic patterns, droughts, floods, and decisions of other water managers.

Use of models inside versus outside observed data range

Use of any econometric model for forecasts inside the range of observed data (interpolation) produces better results than forecasts outside the data range (extrapolation). This study's RRDM is no exception. Application of the RRDM to assess the effects of changes in demographics or site facilities will produce the best results for values of those variables inside the range used to fit the model. For example, the Sacramento District model was fit using visitation data responding to a drought period. The model user should be cautioned that visit and benefit forecasts for the Sacramento District models are expected to be less accurate over a period of several wet years. To some extent, this error can be corrected by use of adjustment or calibration factors, in which the model is set to predict known visits correctly. By starting the model off from a known correct position, management changes in the resource level are expected to produce better results.

These problems can be overcome somewhat by building the database in the first place with wider variation in the range of all the variables. However, this requires more data. In this case, more visitor survey data typically are expensive or unavailable.

Generic versus district specific models

Two sets of models are estimated: generic and region (district) specific. The generic model is estimated with data from all three districts. Region-specific models are estimated only with data from that particular region.

The generic model is estimated for the purpose of producing national transferability to a wide range of potential management applications. For applications of the RRDM to management questions outside the Sacramento, Nashville, and Little Rock Districts, the generic model is expected to produce the most reliable estimates of recreational visitation and benefits. Greater reliability is expected because data for the model are collected over a wide range of demographic, economic, and project operation conditions likely to encompass the range of conditions nationally.

The district-specific models were estimated for the purpose of producing good predictions of management actions within the given district. Thus, for example, a new project may be contemplated somewhere in the Little Rock District, or facility improvements may be considered for an existing project in the Nashville District. For either of those cases or similar ones, the district-specific models are expected to provide the most reliable predictions of visitation and benefits.

Recreation Visits and Benefits

Recreation benefits are derived from visitors' willingness-to-pay (WTP) for recreation trips to USACE projects. Visitors have a WTP value associated with the amount of use of a project. The cost to the consumer of recreation may be user fees, cost of transportation, or the opportunity cost of time. The amount the visitor is willing to pay above the costs to consume the recreation activity is known as the consumer's surplus. Consumer surplus is described more in Chapter 4.

Visitor predictions

Predictions of visits into the future can be done for any number of years. Of course, the accuracy of such forecasts is expected to decrease as the forecast is attempted further into the future. Short-term forecasts are likely to be the most accurate. This report considers long- and short-term RRDM forecasts. In a long-term forecast, predictions are made for many years starting at

a baseline year, where predicted visits have been adjusted to equal actual visits. For short-term forecasts, visit predictions can be constantly adjusted so baseline visit predictions are always accurate. Examples of both types of forecasts are given below.

As one example, a comparison between short- and long-range within-district forecasts is made using the Sacramento District. This district is chosen because annual fluctuations in water levels cause variations in visit totals. In the other two districts, water levels are more constant. Consequently, visits may be more difficult to predict in the Sacramento District. Because 1985 was the last year the Sacramento District was surveyed for the analysis, 1985 is the baseline year. For the long-term forecasts, an annual visit prediction is made for day users and campers for each site from 1986 to 1993. Because the 1985 visit prediction adjustment is used for each site, predicted visits will differ from actual visits. The predictions of the model are compared with known visitation totals at each site. Model performance will be judged based on the accuracy of the predictions. Accurate information regarding all facility levels is assumed. Thus, the actual water levels for the years is used to calculate the variables CV and PCT_FULL. Also, population levels are updated for each year. Other demographic variables are left at the same values used in the original dataset (from the 1980 census data). Finally, travel costs are updated annually using data from the Motor Vehicle Manufacturers Association (1992), but are expressed in 1980 dollars. All benefit values are updated to 1994 dollars using the inflation factor from the U.S. Consumer Price Levels in Table 3 (Federal Reserve Bank of St. Louis 1995).

The years of the prediction (1986 through 1993) generally represent a drought period in the Sacramento District. Except for 1993 (when the drought ended), the water level at most USACE reservoirs was quite low. In 1986, the average value of the variable PCT_FULL for the Sacramento District reservoirs was 92.9. By 1988, the average had fallen to 67.0. Water levels were still low in 1991 (PCT_FULL average of 69.7) but rose dramatically during the 1993 season (PCT_FULL average of 92.3). Because the average value of PCT_FULL during the years the Sacramento District was surveyed (1983 through 1985) is given as 90.18 in Table 5, prediction of visits when PCT_FULL is significantly lower may prove unreliable. Also, CV values were slightly higher during the drought due to extremely low levels late in the recreation season. While most reservoirs were significantly affected by the drought, the impact was minimal at Lake Mendocino. During 1986 through 1993, the average value of PCT_FULL at Mendocino was 97.9. The effect of the drought was also low at Lake Kaweah (PCT_FULL average of 92.0) and Black Butte Lake (PCT_FULL average of 88.3). The drought was especially severe at Success Lake (PCT_FULL average of 42.1), Pine Flat Lake (PCT_FULL average of 54.0), and New Hogan Lake (PCT_FULL average of 59.3).

The long-range forecasts are made for all Sacramento District projects except Englebright and Isabella Lakes due to missing water and visitation

data. The first step in the forecasts is to adjust predicted 1985 visits (day use and camping) for each site to be equal to actual 1985 visitation. This is done by adjusting the constant term in the model. A separate day-use and camping constant term adjustment factor is calculated. The adjustment has the effect of setting predicted visits within the market area equal to calculated visits within the market area. Then the proportions in Table 10 are used to make sure the model predicts total visits correctly, not just total visits in the market area. For example, using the model to predict total Lake Dardanelle visits required multiplying market area visits by 1/0.750 = 1.33. In the long-range forecast scenario, the same site-specific constant term adjustment factors are used for each year of the simulation (1986 through 1993).

The dataset for each site is updated for each year of the prediction using the actual year's data for POPULATION, CV, TOT_COST, and PCT_FULL. The other variables remain constant during the simulations. Using the new data, a visit prediction is obtained for annual day-use and camping visits at each site.

A common test of a model's reliability is to compare predicted results to actual results. In all eight of the double-log models, the basic equation estimated is

$$ln(Y) = \beta_0 + \beta_1*(ln(X_1)) + \ldots + \beta_n*(ln(X_n)) + \epsilon \tag{52}$$

where $X_1 \ldots X_n$, the explanatory variables, are slightly different for each district. The error term is assumed to be normally distributed with a mean of 0 and a variance of σ^2. The sum of all predicted values of the dependent variable, $ln(Y)$, will be 0 (Greene 1993). However, the analyst is usually more concerned with the ability of the model to predict Y rather than $ln(Y)$. Transformation of Equation 52 is carried out by taking the anti log of both sides of the equation. It produces:

$$Y = (e^{\beta_0}) * (X_1^{\beta_1}) * \cdots * (X_n^{\beta_n}) * (e^{\epsilon}) \tag{53}$$

One problem with using Equation 53 to predict the dependent variable is that the expected value of (e^{ϵ}) is not equal to 1.0, and the use prediction will be biased (Stynes, Peterson, and Rosenthal 1986). The term (e^{ϵ}) is log-normally distributed with a mean of $e^{(\sigma^2/2)}$ and a variance of $[(e^{\sigma^2}) * ((e^{\sigma^2}) - 1)]$. The bias enters multiplicatively and is corrected through the constant term. Stynes, Peterson, and Rosenthal (1986) emphasize that the transform bias appears only in the constant term and not in the price coefficient or other elasticity estimates. Thus, estimates of per-user benefits from double-log models will be unbiased. Estimates of total benefits using the predicted visits from the model will be biased, as will predicted use.

Several statistically based adjustment or calibration factors have been proposed in the literature. For example, instead of using the constant term (e^{β_0}),

an asymptotically unbiased constant term ($e^{\beta_0} + s^2$) can be used. If data on actual visits are available, then Stynes, Peterson, and Rosenthal (1986) suggest an empirical basis for adjusting the constant term. This adjustment depends on the ratio of observed visits at a site to the predicted visits using (e^{β_0}) as the constant term.

Predicted visits can be calibrated through the constant term in such a way that the sum over counties equals actual measured visits. Calibration holds much appeal when using the model to assess effects of management action at projects with existing reliable visitation data. Because elasticity estimates are unbiased with proper specification, visit predictions for management changes should use actual visits as a baseline. Using any other baseline may predict unreliable visit changes that are difficult to support for evaluating management actions. It should be emphasized that these calibration factors can be used only on projects for which reliable visitation data are available. When using the model for predicting visits and benefits at new projects, model calibration is inappropriate.

Once predicted visits equal measured visits to correct for bias and produce realistic management recommendations, the next issue is which level of visitation should be adjusted. In the zonal model in this study, visitation can be adjusted at the county level, the project level on an annual basis, or an aggregate project level. For a project surveyed in only 1 year, project level adjustment would consider only that year. If a project was surveyed in multiple years, then the adjustment factor may differ by year.

Three potential applications may require adjustment factors. First, forecasting visitation for any project where visitation is known requires calibrating the constant term. For example, suppose the model predicts 121,600 day-use visits at Black Butte in the Sacramento District, and actual estimated visits in the market area are 206,177. If the model predictions are multiplied by a constant adjustment factor of 206,177/121,600 = 1.69, the model predicts correctly.

Next, the model could be applied to any project in one of the three districts where visitation is unknown, such as a proposed project. However, the reliability of predictions will also be unknown. This application would require a district-level adjustment factor. For example, if the Little Rock District model over predicts visits at existing projects by a factor of 2.0, on average the adjustment factor for a proposed project in the Little Rock District using the model is 0.5, unless more local information is available.

Finally, application to a project with unknown visitation in a different district may necessitate more generic adjustment factors. While it is unclear how the model should best be applied to districts outside the three-district data set, maximum information should be used. For example, if the three-district pooled model over predicts visitation by an average factor of 3.0, the adjustment factor required when applying the model to a project not yet built in any

other district should most likely be 0.33. However, in this case the model reliability is even less certain.

Table 16 presents unadjusted predicted visitation for each site included in the analysis using the parameters estimated for the individual district models shown in Tables 12 to 14. Visitation predictions are averaged for sites surveyed in multiple years. Most unadjusted visit predictions are lower than the estimated visit totals.

Results for long-range visitation predictions are given in Table 17a-h, with percent error of the use prediction given in parentheses. Of the day-use predictions, nearly one-half are within 20 percent of actual visitation and nearly three-quarters are within 50 percent of actual. The camping predictions are slightly more accurate. Again, about one-half of the camping predictions are within 20 percent of actual values but over four-fifths are within 50 percent of actual. Note that predictions for some sites are much better than others. For the three sites least affected by the drought in the Sacramento District (Mendocino, Black Butte, and Kaweah), the average percent error, using the absolute value of the percent error, is 25 percent for day-use predictions and only 18 percent for camping predictions. Meanwhile, the three sites most affected by the drought (Success, Pine Flat, and New Hogan) have an average error of 38 percent for the day-use predictions and 24 percent for the camping predictions. These results suggest that long-range visit forecasts are more accurate if the values of the independent variables are within the range of those used to estimate the model.

The other type of within-district predictions considered are short term. These allow annual updating, so visits are predicted only for 1 year ahead. In this case, visits are adjusted through the constant term, so baseline predicted visits are correct. The same constant term adjustment factor is then assumed for the next year. The annual predictions are again made for the Sacramento District using the years 1986 through 1993. The first predictions are made in 1985 for the year 1986. These predictions are exactly the same as the long-range forecasts above for 1986, because visits are adjusted to equal 1985 visits. However, in the short-term forecasts, predicted visits for 1987 are adjusted so 1986 predicted visits equal actual visits in 1986. The constant term is adjusted annually so visits in year k will always be correct to make a visit prediction for year $(k + 1)$.

An example illustrates how this adjustment is made. Applying the Sacramento District day-use model (presented in Table 14) to Black Butte Lake gives a raw visitation prediction of 121,600 in 1985. The estimated actual total day-use visitation at Black Butte Lake is 235,093 (Table 1), but only 87.7 percent of these visits, or 206,177, occur within the market area. To determine the constant term adjustment factor that makes predicted visits equal actual visits, figure

$$ln\ (206{,}177/121{,}600) = 0.528 \qquad (54)$$

Applying this adjustment factor to 1986 gives a prediction of 200,100 within the market area or 228,200 total. This prediction is too low compared to the actual 1986 visitation of 284,800. In order to make a 1987 prediction, 1986 predicted visits must be adjusted to equal actual 1986 visits. Because the 0.528 adjustment factor is too low, the new adjustment factor must be higher. An additional adjustment, A_a, must be determined such that the following equality holds for the 1986 predictions

$$[\exp(\beta_0 + 0.528 + A_a)] \,/\, \exp(\beta_0 + 0.528) = (Y_a/Y_p) \tag{55}$$

where

A_a = the desired adjustment factor

(Y_a/Y_p) = ratio of actual to predicted visits, for example 2.0 if actual visits are twice observed visits

Cancel terms to produce

$$A_a = ln\,(Y_a/Y_p) \tag{56}$$

So, similar to the original A_d, the additional constant adjustment term is the natural log of the ratio of actual to predicted visits. For the Black Butte example, the log of the ratio of actual to predicted visits is given as

$$ln\,(284{,}800/228{,}200) = 0.222 \tag{57}$$

The final constant term adjustment factor for 1986 would then be 0.528 + 0.222 = 0.750. A similar calculation would be performed every baseline year. The criterion for adjustment is always setting predicted visits equal to actual visits.

Results of short-run visitation forecasts are given in Table 18. The average results are slightly more accurate than the long-range forecasts. About one-half of the day-use predictions are within 20 percent of actual and three-quarters are within 50 percent of actual. For the camping predictions, over half are within 20 percent, while nearly all are within 50 percent. Again, sites least affected by the drought in the Sacramento District had the best predictions. Unlike the long-term scenario, adjustment increased the accuracy of some predictions during the drought. For example, camping predictions for Eastman Lake are more accurate with annual adjustments. The average of the absolute error percentage without adjustment is nearly 100 percent but falls to 25 percent with annual adjustments. Note that the predictions for the nondrought period of 1993 tend to be much larger than actual. When adjusted for drought conditions in 1992, most models proved inaccurate.

Forecast results produce the following conclusions. When conditions at a project are similar from the base to the forecast years, the visit predictions of the model are likely to be most accurate. However, when conditions differ

from those used to construct the models, predictions are typically in considerably greater error. Similarly, visit predictions are more accurate for sites that have nearly constant water levels and minimal variability in water levels within a season.

Adjustment factors for RRDM

Discussion turns next to adjustment factors used for the RRDM. Before presenting concepts and results of adjustment factor calculations, it is important to remember that the market area restrictions are not intended to capture all visitors. Each market area captures a known proportion of total sample visitation for each site. Thus, the sum of all predicted visits should be adjusted to reflect this same proportion of total visitation. Table 10 gives the proportion of total sampled visitors captured by the market areas for each site. The analysis for 5 of the 26 sites includes less than 75 percent of total sampled day-use visitors. For camping visitors, analysis of nine of the sites included less than 75 percent of total sampled visitors. The district averages are a linear average of the sites in the district. Weighing each district equally, the market areas capture an average of 85 percent of all day users and 76 percent of campers. These percentages are used in applications to other districts as described in more detail below.

The constant term is calibrated for the purpose of assuring that total predicted visits for the model equals estimated total visitation within the market area. The unadjusted prediction of total visits, Y_p is based on estimated coefficients. If actual total visits within the market area are estimated to be Y_a, then Y_p needs to be multiplied by a factor of (Y_a/Y_p). The appropriate adjustment factor will satisfy the following equality

$$[\exp(\beta_0 + A_d)] / \exp(\beta_0) = (Y_a/Y_p) \tag{58}$$

where all terms are defined in Equation 55.

Multiply each side by $[\exp(\beta_0)]$ to produce

$$\exp(\beta_0 + A_d) = (Y_a/Y_p) * [\exp(\beta_0)] \tag{59}$$

Because $[\exp(\beta_0 + A_d)]$ equals $[\exp(\beta_0) * \exp(A_d)]$, Equation 59 can be simplified by dividing each side by $[\exp(\beta_0)]$ to get

$$\exp(A_d) = (Y_a/Y_p) \tag{60}$$

Take the natural log of both sides to solve for A_d as

$$A_d = ln\,(Y_a/Y_p) \tag{61}$$

Therefore, based on the intercept term presented in the Tables 11 through 14, the intercept is adjusted as shown in Equation 61. For example, turn to the

intercept in Table 12 of 0.240 for the day-use Little Rock model. If actual day-use visits at Beaver Lake were twice as high as predicted, then $A_d = ln(2.0)$. That is $ln(2.0) = 0.693$ should be added to the intercept. The modified intercept would be $0.240 + 693 = 0.933$, to predict correctly. The adjustment factor is simply the natural log of the ratio of actual visits to predicted visits.

Consider the first situation where adjustment is necessary: forecasting for a site with known observed visitation. This site may be included in the three-district analysis of this study or an unstudied site in another district. In either case, visit predictions in the present year can be adjusted using Equation 61 so the total equals actual visits. From manager's perspective, the important factor to consider is that a credible baseline is used (predicted equal actual visits).

For example, suppose one wishes to forecast visits for a studied site in the Little Rock District several years after the study data were collected for a certain policy proposal. The Little Rock models are based on data from 1985, but the policy forecast might originate in the present year (1994). For a particular site, take the day-use and camping Little Rock models presented in Table 12 and adjust the constant term and market area totals so predicted 1985 visits equal actual 1985 visits. A separate adjustment factor for the day-use and camping models would be obtained.

Before the model can be used to forecast for future years, the models should be updated to the current year (e.g., 1994). Predicted visits in 1994 should match observed visits in 1994 before proceeding to forecast. The adjustment factors that correct the model's predicted visits in 1994 will not equal those factors used to correct 1985 visit predictions. Differences in adjustment factors present an indication of the reliability of the models over time. A stable adjustment factor over time seems to support a model that can be applied reliably over time. An unstable adjustment factor may indicate that the coefficients of the model are changing over time and the ability of the model to forecast future visits is weak.

Because nearly 10 years of data exist between the surveyed years and the 1994 application, the stability of the adjustment factors over time was tested. Predicted visits can be adjusted to equal actual visits for the last year a site in this analysis was surveyed. For example, Hensley Lake was last surveyed for this study in 1985. Predicted 1985 visits can be adjusted to equal 1985 actual visits for both day-use and camping visitors using Equation 61. The resulting 1985 adjustment factors can then be applied to simulated visit predictions from 1986 to the present using values of the independent variables for the appropriate years. Thus, a 1985 forecast using perfect information of the future is made for the years 1986 to the present. Simulated visit predictions are compared to actual visit totals. Visit predictions similar to actual visit totals indicate that reliable forecasts can be made with the models. However, if simulated predicted visits are greatly different from actual visits, then using the models for forecasting future visits is limited. Nevertheless, the model can be

used to evaluate the consequences of resource management actions if visits are calibrated correctly.

From this finding, a confidence interval for forecast visits is obtained. Also, trends may become evident. For example, predicted visits may remain constant while actual visits continue to increase. This may signify that a shift in recreation preferences not explained by the variables included in the models is occurring.

For a second type of management application, visitation at a site in one of the three districts is unknown. Because visitation can be adjusted such that predicted visits equal actual visits, information from the other sites in the district must be used. An average adjustment factor for the district can be calculated from the site-specific adjustment factors. Note that the individual site adjustment factors may vary significantly within a district. If so, then predicting visitation for a site with unknown visitation will be subject to error. For districts with widely variable adjustment factors, it is best to choose an adjustment factor from a similar site rather than the district average.

The final management application that requires adjustment factors is applying the models to sites in other districts with unknown visitation. Average adjustment factors can be calculated for the pooled models. This case is similar to the above situation, but the likelihood of large errors is greater. Underlying recreation behavior in different districts may be dissimilar from the three study districts included in the models. In fact, recreation behavior in the three districts included in this study may be different.

Table 19 reports the average adjustment factors for all sites included in this analysis. For sites surveyed in multiple years, the adjustment corrects total visitation over all survey years. The adjustment factors are calculated using Equation 61 based on the natural log of the ratio of estimated total visits in the market area to predicted visits within the market area.

A positive adjustment factor means that predicted visits are less than actual visits. Of the 26 sites included in this analysis, negative adjustment factors result for only 5 sites for day-use visitation and 1 for camping visitation. Thus, using a positive adjustment factor for a site with unknown visitation provides nearly 90 percent confidence that the adjustment is in the correct direction.

Because the adjustment factors involve an exponential function, small differences in the adjustment factor can reflect large differences in the ratio of actual visits to predicted visits. For example, for the camping model in the Little Rock District, Beaver Lake has a constant term adjustment factor of 1.209, while Blue Mountain Lake is 1.671. These values appear similar in exponential form. However, the ratio of actual to predicted visits for Beaver Lake is 3.4, while the ratio is about 5.3 for Table Rock Lake.

An average adjustment factor is given for each district. This value is not the linear average of the site values given in the table. A manager would want to predict actual visits on average rather than the log of actual visits. The appropriate district average is then based on the average ratio of actual to predicted visits. The district average adjustment is calculated as the natural log of the average ratio of actual to predicted visits for sites in that district.

For management applications to sites in other districts with unknown visitation, more general adjustment factors are required. Note that these generic factors are not necessary for forecasting situations at sites with known present visitation, in which case, the adjustment factors can be calculated for the present and the same adjustment used in forecasting. In any forecasting situation where present visitation is known, adjusting of the models is a two-stage process. First, apply the overall market area proportions to estimate the number of visitors occurring in the market areas. Thus, the 125-mile day-use market area should contain about 85 percent of all day users, and the 175-mile camping market area should capture 76 percent of all campers. Once these proportions of total visitation have been calculated, then the constant term can be adjusted to sum to these totals.

Universal adjustment factors would be applied to sites in other districts with unknown visitation, such as a proposed site. Because the pooled models in Table 15 would be used for sites outside the three districts, adjustment factors need to be based on these models. The universal adjustment factors are calculated by first obtaining an unadjusted visitation prediction for each site (day use and camping) using the pooled models. These predictions are given in Table 15. Predictions are summed for sites that were surveyed in multiple years.

The next step is to determine the amount of day-use and camping visitors originating within the market areas for all sites. The total visit estimates in Table 1 and the proportion figures in Table 10 can be multiplied to obtain estimates for the number of day-use and camping visitors originating within the market areas. The constant term adjustment factor is then calculated as the natural log of the ratio of estimated total visitation in the market area to the visit prediction in Table 20.

Consider an example of this calculation. Table 1 gives the total number of 1985 day-use visitors to Norfork Lake (in the Little Rock District) as 2,985,276. Table 10 shows that 0.710 of all day-use visitors to Norfork Lake originate within the 125-mile market area. Thus, an estimated 2,119,546 day-use visitors originated within the market area. The pooled day-use model prediction for Norfork Lake from Table 20 is 1,304,600. The ratio of actual to predicted visits is 2,119,546/1,304,600 = 1.625, and the natural log of the ratio is 0.485. Thus, for Norfork Lake, the day-use constant term should be adjusted upward by 0.485 (from -10.151 to -9.666), as shown in Table 21. Note that the constant term of -10.151 comes from the model results in Table 15.

Performing the above calculation for every site gives the adjustment factors presented in Table 21. To calculate an average, again find the natural log of the average ratio of actual to predicted visits rather than the average of the natural log of actual to predicted visits. The average ratio of actual to predicted visits for day-use visitors is 3.861, and the natural log is 1.351. For campers, the average ratio is 3.034, and the natural log is 1.110. The universal constant term adjustment factors are 1.351 for the pooled day-use models and 1.110 for the pooled camping models. On average, these adjustments should produce market area predictions that include about 85 percent of all day users and 76 percent of campers.

As the above discussion suggests, application of the models is not straightforward and some discretion is necessary. Several simulations detailed in this chapter show how to apply the models to different management situations and highlight ways to overcome possible difficulties. Table 21 summarizes the different constant term adjustment factors to be used in different policy applications.

Benefits per visit

Consumer surplus is measured as the area under the demand curve above the fee level as discussed in Chapter 4. Total benefits are fee revenue plus consumer surplus. For day users to the USACE sites included in this analysis, no fee is presently charged (early 1994). However, fees are charged for camping. These fees must be considered in estimating total benefits but are not a part of consumer surplus.

Unbiased estimates of per-user benefits can be obtained using the unadjusted models for sites where visitation is known. The per-user benefit is then multiplied by the number of known visitors to get an unbiased estimate of total benefits, where visits totals are known. Otherwise per-user benefits are multiplied by predicted visits using an appropriate calibration factor. To calculate the per-user benefit of any given study project, first consider the model used to predict visitation

$$Y_0 = \exp(\beta_0) * (\mathrm{TOT...COST}_0^{\beta_{TC}}) * (X_2^{\beta_2}) * \cdots * (X_n^{\beta_n}) \qquad (62)$$

Equation 62 is used for illustration only. However, it is similar to all eight models actually fitted. In Equation 62, $\mathrm{TOT\_COST}_0$ is the estimated travel cost to the project from a particular county; the X's are values of the other predictor variable and the β's are estimated parameters. Y_0 is the unadjusted visitation prediction. Actual visit predictions are given in Table 16.

Total consumer surplus is computed as the definite integral of Equation 62. The integral is evaluated at each county from $\mathrm{TOT\_COST}_0$ up to a travel cost value that would reduce visits to a negligible level. Define this travel cost as

TOT_COST_{max}. A table of integrals shows that total benefits for any given county equals:

$$\text{Benefits} = [(Y_{max} * TOT\_COST_{max} / \beta_{TC} + 1)] - [(Y_0 * TOT\_COST_0) / \beta_{TC} + 1)] \tag{63}$$

where

Y_{max} = number of visits that the model predicts at TOT_COST_{max}, the threshold travel cost

If TOT_COST_{max} is set to an arbitrary high level, Y_{max} is 0, and the first term of Equation 63 is 0 for values of β_{TC} not equal to -1.0. In this case, the estimate of total benefits reduces to the much simpler expression

$$\text{Benefits} = -[(Y_0 * TOT\_COST_0) / (B_{TC} + 1)] \tag{64}$$

The issue of what value to use for the maximum travel cost is contentious and to date unresolved. Some previous studies suggest using a finite maximum travel cost. Smith and Kopp (1980) propose using the maximum observed travel cost in the sample. This choice assumes that at higher prices, no visitors are observed and no consumer surplus accrues to those visitors.

Despite the Smith and Kopp findings, there is some rationale for using a maximum price higher than the maximum observed travel cost. Even beyond the highest sample travel cost in the specified market area, TOT_COST_{max}, single-destination travelers may still be observed. Analysis of visitor data obtained from the Missouri River Division of USACE (Appendix A) supports this concept. From Appendix A, 90.9 percent of all single-destination travelers are captured using a 125-mile day-use market area and a 175-mile camping market area. If both market areas are doubled, then the amount of single-destination visitors included jumps to 95.8 percent. In the Missouri River Division, about 5 percent of all single-destination visitors originate between the actual limits of the specified market area and double the market area limits.

Using the maximum observed travel cost as the threshold price as described assumes conservatively that no visitation would occur at these distances because no consumer surplus is generated. For this reason, truncating maximum travel cost at the high end of the chosen market area produces conservative estimates of total benefits.

Average benefits per user, when summed over all counties of origin, are calculated by dividing Equation 63 by predicted visits (Y_0). These per-user benefits are computed as

$$AB = \frac{\sum_i [(Y_{maxi} * \text{TOT\_COST}_{max})/(\beta + 1)] - [(Y_{0i} * \text{TOT\_COST}_{0i})/(\beta_{TC} + 1)]}{\sum Y_{0i}} \qquad (65)$$

where

AB = average per-user benefits, and the summation occurs over the county index, i

Note that the term $\beta_{TC} + 1$ is a constant. Therefore Equation 65 can be expressed as

$$AB = \frac{(\beta_{TC} + 1) \sum_i (Y_{max} * \text{TOT\_COST}_{max}) - (Y_{0i} * \text{TOT\_COST}_{0i})}{\sum_i Y_{0i}} \qquad (66)$$

Average benefits per user are thus shown to depend on actual and maximum travel costs, the estimated coefficient on travel costs, and predicted visits at both the actual and maximum travel costs.

This study takes a conservative stand on benefit estimates by using the maximum observed travel cost in the samples as TOT_COST_{max}. For the day-use models, TOT_COST_{max} is \$26.13 for the Little Rock District (1980 dollars), \$27.14 in Nashville, and \$25.92 for the Sacramento District. For the camping dataset, TOT_COST_{max} is \$34.58 in the Little Rock District, \$43.58 in Nashville, and \$38.60 in Sacramento.

Average per-user benefits for each project are presented in Table 22. The benefit numbers shown in Table 22 have been multiplied by 1.80 times the values obtained by directly applying Equation 66. Benefits are thus expressed in 1994 dollars using the 1980 through 1994 inflation factor in Table 3. For sites surveyed in multiple years, the values reflect an average. District averages are weighted by visitation across sites. The per-user benefits in Table 22 should be viewed as conservative. Actual single-destination visitors who came from beyond the maximum market area threshold prices were treated equally as market area visitors in the benefit calculations.

To test the sensitivity of benefits per user to the threshold price changes, a price doubling is presented. Actual observed travel cost is not changed. Per-user day-use benefits increased by an average of 11 percent for the Little Rock District, 20 percent in the Nashville District, and 10 percent in the Sacramento District. The per-user camping benefits increased by an average of 44 percent in the Little Rock District, 89 percent in the Nashville District, and 31 percent in the Sacramento District. Thus, using a higher TOT_COST_{max} makes only a small difference for the day-use benefits at a site

but may increase camping benefits considerably. This issue is discussed further in the next section when total site benefits are presented.

Total benefits

Using the log specification, total benefit values can be calculated using the unbiased per-user benefits multiplied by an independent estimate of total visitation. Using this method, the visit totals presented in Table 1 are multiplied by the corresponding per-user consumer surplus (benefit) estimates in Table 22 to obtain total benefits. Results are shown in Table 23. For example, at Beaver Lake in 1985, total day- use visits of 3,521,856 in Table 1 are multiplied by benefit per user of $1.87 to produce $6,592,860 estimated total benefits in 1994 dollars.

Generally, sites in the Nashville District produce the highest overall recreation benefits due to high visitation and high benefits per visit. Projects in the Sacramento District have the lowest benefits. However, recreational values per acre foot of water are quite high in some cases, for reasons to be discussed in Chapter 5. Even though significantly fewer campers tend to visit a site compared to day users, camping benefits contribute approximately 35 percent of total site recreation benefit. Again, all benefits are in 1994 dollars.

As described in the section above, all benefits in the estimation sample are calculated using a conservative maximum observed travel cost. Using a higher maximum price, such as double the maximum observed travel cost, will increase total consumer surplus. While day-use consumer surplus will increase only slightly by using a higher choke price (maximum market area), camping benefits may increase significantly (nearly doubling in the Nashville District). Using double the maximum observed travel cost as the maximum price would result in total benefits of about $92 million in the Little Rock District, $297 million in the Nashville District, and $34 million in the Sacramento District in 1994 dollars. Averaged across the three districts, using double the maximum observed travel cost as the maximum price will increase total consumer surplus by about 30 percent.

The final factor to consider in estimating total site benefits is fee revenue. While no day-use fees were collected at any of the sites during the survey years, camping fees were collected. While exact revenue values are not presented, the national average for camping fees at USACE sites in 1985 was $5.92. This converts to $4.53 in 1980 dollars. Note that every camper does not pay the equivalent of $4.53 in camping fees. Rather, the camping fee is collected from the entire visitor party. Data on average number of visitors per vehicle is available from the visitor surveys. An average was calculated for each site. The total number of camping revenue payments is assumed to equal the total number of camping visitors divided by the average number of visitors per vehicle. Table 24 gives the estimate of total camping revenues and total economic benefits for each site updated to 1994 dollars. Total

benefits are equal to the camping revenues plus the consumer surplus totals from Table 23.

Camping revenues tend to constitute a small portion of total economic benefits. In the Little Rock and Sacramento Districts, camping revenue receipts comprise about 10 percent of total economic benefits, while in the Nashville District, the proportion is only about 4 percent. This evidence suggests that fees collected at recreation sites produce a very small percentage of total economic benefits. Instead, consumer surplus constitutes by far the greatest majority of total economic benefits of recreation sites at USACE projects (Chapter 4). Put differently, under current pricing policies at USACE projects, over 90 percent of recreation benefits received by onsite users are free.

Incremental benefits from facility improvements

Recreation managers are typically required to allocate resources across competing opportunities. One important issue, especially in the Sacramento District, concerns the economic value of water for different competing uses, such as municipal water supply, irrigation, hydroelectric power, and fish and wildlife habitat.

The calculation of incremental benefits resulting from a one-unit addition to any of the facilities is simplified because only the change in predicted visits needs to be estimated. Appendix E graphically illustrates application of the RRDM to selected management issues. Per-user benefits are independent of the level of facilities using this study's demand equation. To show this, refer to the term for per-user benefits given in Equation 66. With a change in facility levels, the parameter estimate for the travel cost variable and both actual travel costs and maximum travel costs from the edge of the market area remain constant. The second term in Equation 66 remains constant. The only terms that change from facility improvements or reductions are Y_{max} and Y_0.

To see why resource qualities (facilities) have no effect on benefits per user, suppose that a certain facility variable has a value of m. For example, suppose a project has m = 200 picnic tables. This variable enters into the visit predictor Equation 62 multiplicatively as (m^{β_m}), where βm is the estimated elasticity of the facility. Increasing the value of the picnic tables to $(m^{\beta m})$, $(m + 1) = 201$ will cause visits to increase by a factor of $[((m + 1)^{\beta m})/(m^{\beta m})] = (201)^{\beta m}/(200)^{\beta m}$. Predicted visits at both the actual and maximum travel costs will increase by the same proportion. Because these two terms are expressed as a ratio in Equation 66, the ratio remains constant and per-user benefits are unaffected by a change in the facility level. Thus, if picnic tables are increased from 200 to 201, users and total benefits increase by the same proportion and average benefits per user are unaffected.

The unadjusted model predictions can be used to calculate the incremental value of one more unit of any project variable because the constant term adjustment factors are also multiplicative. To calculate this incremental value of a project variable (e.g., water quantity), begin by recording unadjusted visit predictions. Then, add a value of 1 to the particular facility variable under study, e.g., one more surface acre of water. The ratio of new predicted visits to original predicted visits is recorded. The predicted change in visits is multiplied by the average benefit per visit to produce an estimate of the incremental value of one more unit of the project variable in question. This method of analysis is used to estimate incremental values of one more unit of all the project variables that entered the model. Results are in Tables 25a through 25f. For example, in Table 25a, the incremental annual benefit of one more full service marina at Beaver Lake is $96,000. In Table 25b, the annual value of increasing swimming beaches from 11 to 12 at Beaver Lake is $33,700. The other Tables 25c through 25f have a similar interpretation.

Several assumptions are implicit in the calculation described. First, there must be a demand for the additional facilities. If facilities are never fully utilized, then the incremental value of additional facilities is 0. Second, the increase in facilities is assumed to have no negative impacts on visitation for factors not included in the model. For example, construction of additional parking facilities is assumed to have no adverse affect on the visual quality of the recreation site, that is a factor not in the model. It is also assumed to have no effect on other quality variables in the model. For instance, because picnic tables are statistically important in the day-use models but not the camping models, only day users are presumed to benefit from picnic tables.

Finally, the model does not directly consider the impact on crowding from additional facilities. The positive coefficient on each facility variable indicates that visitation will increase at a decreasing rate as the facility level is increased. The model will never predict that visitation will decrease with increases in facilities.

Tables 25a through 25f also present estimates of the incremental value of improving all facilities at all projects by a single unit. These values are discussed over the next few pages. Results on several of the facility variables presented in these tables provide a check on the plausibility of the estimated coefficients. Despite estimated elasticities, a one-unit increase in certain facilities may nevertheless have physical limits on the amount of additional visitors that can be accommodated from that improvement. While beaches and marinas can be used by many visitors at once, other facilities can only be used by one group of visitors at a time. A parking space can only contain one car at a time. Physical limits also exist for boat launch lanes, picnic tables, and camping sites. For the visit increase predictions to be plausible, physical limits of the facilities should not be exceeded.

If a day-use parking space is used by three vehicles per day with four individuals per vehicle, then 12 visitors per day can use a parking space. If the space is used 250 days per year, then an upper limit of about

3,000 visitors per year can use one parking space. As shown in Table 25e, model-predicted visits from a unit increase in parking spaces are well below this limit. Thus, the model predicts that additional parking spaces will not be used to capacity. It is of some interest to note that the most additional visitors for a unit increase in parking spaces for any study project is 640 at Lake Kaweah in the Sacramento District (Table 25e). In fact, Sacramento District office plans additional parking spaces for Kaweah to ease congestion during peak periods. The value of parking spaces at Kaweah is discussed below.

For boat launch lanes, Joe Holmberg[1] estimates that up to 40 daily launches can be made at a launch lane. If 6 visitors are in each boat and a launch lane is used 250 days per year, then a maximum of about 60,000 additional visitors should be expected with a new launch lane. All but a few predictions in Table 25c are below 60,000 visitors, with a low of 770 at Table Rock Lake. The maximum amount of visitors predicted is 88,000 at Lake Kaweah. High demand for boat launch lanes is evident at several sites in the Sacramento District. A recreation manager at these sites can best determine if the visit predictions are reasonable.

In cases where the predictions of the models appear unrealistic, qualitative interpretations may still provide insight. For example, if the prediction of 83,160 per anum new visitors at Lake Mendocino produced by one new boat launch lane stretches the bounds of credibility, the model still provides the signal that demand for additional lanes is higher at Mendocino than at most projects.

Picnic tables are also only useable by a limited number of visitors. If a table is used by four groups of day users per day and each group has a maximum of eight people, then about 30 day-use visitors could use a picnic table in 1 day. If a table is used 250 days per year, then a maximum of about 8,000 visitors can be accommodated annually by a picnic table. This limit is exceeded only at Norfork Lake in the Little Rock District, when an added table generates a predicted 15,850 added visitors (Table 25f). Most sites have predicted visit increases of less than 3,000.

Finally, camping sites can only be used by one visitor group per day. Because USACE records indicate that campers stay an average of 2.43 days, a camping site used 250 days per year should accommodate about 100 camping groups per year. If each group contains about five visitors, then about 500 campers can use a camp site annually. In response to an additional camping site, the maximum number of predicted visitors is 450 at Millwood Lake in the Little Rock District (Table 25d). The average predicted increase in visitors is about 120.

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[1] Personal communication with Joe Holmberg, Chief, Natural Resources Management, Sacramento District, 1994.

In all but a few of the visit predictions, the values are within the bounds of reasonable physical limits. The plausibility of the visit predictions support the validity of the coefficients on the facility variables. Of course, a better test is to count actual visit changes as a result of installing added facilities.

Another application of the model involves estimating the economic impact of selected management actions for the purpose of cost-benefit analysis. Examples of proposed management actions include various water management schedules and adding or removing facilities. An example presented below illustrates how to analyze such actions.

A recent (1994) proposal has been made to construct additional parking facilities at Lake Kaweah in the Sacramento District. Present crowding leads many visitors to park along nearby roadsides. A total of 130 new parking spaces have been proposed for construction, which would increase the total number of parking spaces to 379. The positive parameter estimate on parking spaces in the Sacramento day-use model (0.243) implies that additional parking spaces will attract more day-use visitors. Note that additional parking spaces will not affect the predicted number of campers according to the assumptions of the model.

The first step in determining the economic benefit of the additional parking spaces is to adjust the model so predicted visits equal actual visits for the most recent year (1993). Using the Sacramento District day-use model and substituting in the 1993 values for POPULATION, CV, TOT_COST, and PCT_FULL, the unadjusted within-market area visit prediction for Kaweah is 169,800. Actual day-use visits at Kaweah in 1993 are 603,500. Using the 0.842 proportion of visits that occur within the market area (from Table 10), estimated actual visits within the market area are 508,100. The calculated constant term adjustment factor then becomes

$$ln\ (508{,}100/169{,}800) = 1.096$$

Thus, the correct day-use visits for Kaweah for 1993 are predicted by using a constant term of 6.956 (the value given in Table 14) plus 1.096, or 8.052. With this adjustment factor, the model predicts the correct 508,100 day-use visits.

Once the correct visits are predicted by the model, the value of PARKING is increased from 249 to 379. The model, still with the adjustment factor of 1.096, then produces a within-market area visit prediction of 562,400. Expand this to obtain total predicted visits by multiplying by (1/0.842), or 1.188. This produces a total for predicted visits of 668,100. This represents about an 11 percent increase in total annual visitation due to the additional parking spaces. Using the integration procedure described previously, the per-user consumer surplus for day users at Lake Kaweah in 1993 is given as \$1.38 (1980 dollars). The annual benefit of the additional parking spaces is

$$\$1.38 * (668{,}100-603{,}500)] = \$89{,}100$$

This amount of $89,000 is updated to $160,200 in 1994 dollars using an adjustment factor of 1.80 to account for inflation between 1980 and 1994 (Table 3). The $160,200 recreation benefits produced by the additional parking can be compared to the annualized equivalent cost of installing, operating, and maintaining the facilities to decide whether their additional benefits exceed their additional cost at Lake Kaweah.

In using the described method of forecasting analysis of management actions, several points should be kept in mind. First, using of the double-log algebraic functional form model has the effect of producing a constant value of benefits per visit under all levels of site facilities.

Second, the benefit estimates do not consider any external benefits or costs, such as environmental or scenic impacts. Installation of parking spaces may decrease the aesthetic quality of a site, but the ability to estimate these costs lies outside the scope of the model. Also, the model assumes that other facilities are not limiting factors to visitation. For example, an increase in parking spaces may provide little benefit if facilities do not exist to accommodate the additional visitation. The importance of these various points is perhaps best determined by site-level recreation managers who have the opportunity to observe visitor behavior. Site-level visitor surveys may also be a useful complement to the modeling approach described in this report to obtain input on potential management actions.

Effect of Emerging Demographic Patterns on Visitation

In addition to project variables, travel costs, and substitutes, visits to USACE projects depend on numerous demographic factors. Forecasting visits based on projections of these factors are performed similar to forecasts of visits based on changes in a site-level variable. However, for this case the site-level variables are held fixed. Projected demographic factors projected may include population, income, age structure, and ethnic proportions. Forecasting the consequences of visitation at USACE projects resulting from anticipated changes in demographic patterns in a project's market area is an important issue. To perform such a forecast, the model user only needs to insert new values for these demographic variables in the visit prediction model to obtain new visitation predictions.

The nation's demographic makeup is projected to change in ways that will impact visitation to recreation sites such as USACE reservoirs. In particular, the U.S. population is getting older, becoming more diverse, and growing. The models estimated for the Nashville District indicated that counties with higher minority populations (defined as percent black plus percent hispanic, as reported by the U.S. Bureau of the Census) visited the sites at lower rates, both for day use and camping. Counties with older populations (high proportion with age greater than 65) showed lower day-use visitation rates.

To investigate the influence of these demographic changes, long-range visitation projections were made for the Nashville District for the years 1990, 1995, 2000, 2005, and 2010 (Table 26). For these projections, the variables POPULATION, OVER_65, and MINORITY were projected to change at the same rate as is projected for the entire U.S. by the Bureau of the Census. Over this period, all three variables are projected to increase. By 2010, population is projected to be about 1.25 times 1985 levels, resulting in more recreation visits. This increase due to population growth will be offset, however, by increases in age and minority makeup, that by themselves will depress visitation rates. The percent of the population over 65 is projected to increase by a factor of 1.18 by the year 2010. The percent black is projected to increase by 1.13 and the percent Hispanic by 1.71. The net effect of all three projected demographic changes described above is about a 10-percent increase in visitation over the period 1985 to 2010.

Visitation data for 1990 can verify the accuracy of these projections. The 1990 projected visitations are about 2 percent higher than actual visitation in 1985. In reality, most sites in the Nashville District experienced an increase in visitation of about 20 percent between 1985 and 1990. Visits for two sites nearly doubled during this period, and visits at Laurel River Lake tripled. The 1990 forecasts (Table 26) are lower than actual 1990 visit totals in all cases. Whether these projection errors are the result of fundamental changes that have occurred in the tastes and preferences of visitors or the result of short-term changes in unmeasured variables such as weather remains to be seen.

Impacts of User Fees

A basic assumption of the travel cost model is a visitor's response to an increase in travel costs at a given project is the same as an increase in the entrance fees at that project. A $1 increase in user fee is presumed to cause visitation to change by the same amount as a $1 increase in travel costs from the visitor's home to that project. Consequently, the visitation impact of a user fee is estimated by increasing the value of TOT_COST for each county in the market area. Other demand predictors, such as the travel cost to substitute sites or qualities at the project and at substitutes, are held constant.

To calculate the impacts of a change in entrance fees, begin with a calibrated model that sets predicted visitation equal to actual visitation at a given project. Predicted visitation with the entrance fee is then estimated by adding the amount of the proposed entrance fee to the variable TOT_COST for that project only.

The impact on benefits resulting from a change in entrance fee is more complicated than the impact of changes in a facility variable described above. Consider the example of increasing the entry fee by $2 per trip. With a resulting change in TOT_COST of $2, Equation 66 shows that per-user benefits will change. Per-user benefits tend to increase with fee increases, though

decreases are possible. TOT_COST_{max} in Equation 66 is still used correctly as the upper limit of travel cost from visitors at the edge of the market, so it is unaffected by the $2 fee. Therefore, TOT_COST_{max} is still the correct price over which consumer surplus is measured. However, the value of observed travel expenditure, TOT_COST_0, will increase by $2 as a consequence of the added $2 entrance fee. Figure 3, in Chapter 4, shows that total benefits decline with an increase in entry fee. That is, even if per-user benefits increase with a fee, total number of users decrease by a greater percentage.

Campers and day users are expected to have quite different responses to a fee change. Campers were charged fees at the time of the surveys in the late 1980's, and the analysis below considers the impact of an increase in fees. In all models estimated, the elasticity of visitor demand is considerably higher for day users than campers. Thus, our results suggest that day-user visitation will decrease by more than camper visitation in response to a similar fee increase. This behavioral response is expected because any imposition of fees upon day users represents a significant change from no fee. Because campers already pay a fee, price elasticity (response) of demand is higher for day users. Also USACE camping fees are typically lower than substitute camping opportunities, so camper visitation should decrease more moderately than day-use visitation with equivalent fee increases.

Tables 27a and 27b display how visitation is predicted to change with an increase in fees per visitor. An increase of fees from $0.25 to $3.00 per visitor is analyzed in five increments. Effects resulting from fee per party can be completed by dividing by average party size. Values represent the proportion of observed visitation at a particular fee level in relation to baseline fees. Fee increases are measured in 1980 dollars for consistency with the rest of the model. Also, fees for overnight visitors are normally charged on a per-party basis rather than a per-visitor basis.

Table 27a shows that day-use visitation is predicted to decrease significantly if large day-use fees are imposed. Fees are measured in 1992 dollars for the sake of illustration. Visitation is typically predicted to decrease by one-half if a $1.00 per-visitor fee is charged; with a $3.00 per-visitor fee, only about 20 percent of initial visitation is typically predicted. Other estimated visitation responses to a variety of potential day-use fees are also included.

Camping is less affected than day-use by fee increases (Table 27b). A $1.00 per-visitor fee increase is typically predicted to cause less than a 20-percent loss of camping visitation. Because of the typically lower price elasticities for campers, camping visitation can still be at 50 percent of baseline even with a $3.00 per-visitor fee increase.

An example illustrates how a change in per-vehicle fees can be analyzed by the model. Suppose USACE wishes to analyze the impact on visitation of a $2.50 day-use fee at Eastman Lake in the Sacramento District compared to actual visits measured in 1992. (In 1994 user fees of $2.00 were charged for

use of boat ramps and beaches.) The first step is to convert the increase into 1980 dollars because 1980 is the base year for estimating the RRDM. The Federal Reserve Bank of St. Louis (1995) gives a deflation factor of 0.587 from 1992 to 1980 dollars. That is each 1992 dollar is only worth about 59¢ in 1980 dollars. The \$2.50 increase in 1992 translates to a \$2.50 * 0.587 = \$1.47 increase in 1980 dollars. All individuals in a vehicle are presumed to share entrance fees equally, similar to travel costs. Because the average vehicle at Eastman Lake contains 2.93 people, the average increase in per-user costs from the entrance fee is \$1.47/2.93 = \$0.50 in baseline 1980 dollars.

The model predicts that day-use visitation at Eastman Lake will decrease to about 78 percent of the visitation level that would result with no entry fee (Table 27a); actual day-use visitation at Eastman Lake in 1992 was 48,700 (Table 18b). For this reason, if a \$2.50 day-use fee is charged, the 78 percent translates to 37,986 visits with the fee. A similar analysis could be performed for fee impacts on visitation forecasted for any year, e.g., 1995 or 2000.

As discussed above, per-user benefits change for different fee levels. Benefits per user (total benefits divided by total users) tend to increase as the fee level increases, though decreases are possible. In some cases, benefits per visit increase by 50 percent or more for a large fee increase. That is, fee increases tend to reduce total visits by more than total benefits. Where this occurs, benefits per remaining visitor are higher with than without the fee increase. Even with a \$1.00 fee increase, a 20-percent increase in per-user benefits is common. However, whether or not benefits per visit increase with a greater fee per visit, total recreation benefits fall wherever fees are imposed (as long as congestion is not an issue).

Figure 3, in Chapter 4, indicates the relationship between total benefits, the fee per visitor, and total fee revenues. The figure shows that any increase in fee per visitor must reduce total recreation benefits. If congestion is not a problem, total recreation benefits to the public is maximized when the entry fee is zero. However, zero fees are not always desirable, because resulting revenues to the treasury are also zero. For this reason, the change in total recreation benefits in response to an implemented user fee should be included in an objective cost-benefit assessment of the action.

One striking result found with the entry fee management applications was the proportion of day users that come from origins very close to the project. It would appear that while local residents are using the project extensively, many of the visits are for low-valued purposes, such as a place to eat lunch, a park for taking the kids, that do not generate high economic benefits. While more distant visitors visit less frequently, the higher travel costs assure that only high-value trips, typically involving water craft are taken.

A consequence of this pattern is that an access fee causes a greater decrease in the percentage of trips for close-by origins than for distant origins. This asymmetric effect of access fees can be illustrated by comparing two

counties of origin, one with travel costs of $2 per trip, the other with travel costs of $10. Using our estimated price elasticity of demand from the pooled day-use model (-3.352 in Table 15), an increase in the access fee of $0.20 would increase costs for the first county by 10 percent, resulting in a 34-percent decrease in visits. That same increase of $0.20 would increase costs for the distant county by 2.0 percent resulting in a decease in visits from that county of about 2.0 * 3.4 = 6.8 percent. Thus, visitors from local origins account for most of the reduction in visitation that occurs as a result of an access fee increase.

These findings have implications for how a fee could be collected. A fee collected only from visitors who use more high-valued facilities, such as boat ramps or developed beaches, would impact visitation far less than a more widely implemented fee, as it would allow nearby residents to continue to use the project for low-benefit uses, such as picnicking, without paying the access fee. Similarly, some sort of season pass might be a low-cost way for nearby residents to escape the most onerous effects of visit-by-visit fees.

The same pattern was less evident in camping visits. While nearby residents use camping facilities more than distant visitors, the pattern of high numbers of low-valued trips is less pronounced than for day use. This result occurs because increased travel distance or increased entry fees have a more moderate effect on reducing camper use than on day use.

Effects of Reservoir Fluctuation on Visitation and Benefits

An important site variable to consider is water. Water is a resource for which wise management is central to the mission of the USACE. Water enters into the visit predictor regression equations through two variables: SUR_ACRES and PCT_FULL. While SUR_ACRES is the fixed design size of the recreation pool, PCT_FULL can be varied by changing the water level at a project. Thus, PCT_FULL is the appropriate variable to use in calculating the incremental value of reservoir management actions affecting water contents of a given project.

Water is valued in terms of benefits per acre-foot for this study. This unit of value allows direct comparison among competing water users at numerous locations, which is important in arid regions. A change in PCT_FULL of one unit translates to different changes in surface acres at different reservoirs. For example, adding 1-percent surface acres at a 1,000 acre reservoir has one-tenth the added acres compared to a 10,000 acre reservoir.

The analysis converts incremental recreation benefits into added benefits per acre-foot of water using the PCT_FULL variable in several steps. The first step to estimate the incremental value from an added acre-foot of water is to calculate the added benefits from increasing PCT_FULL by one unit.

Because PCT_FULL is not a fixed facility variable like picnic tables, the baseline level of PCT_FULL can vary at a given project, even over a short time. The incremental value of increasing PCT_FULL by one unit will differ according to its baseline level. For this reason, the incremental value of more water is evaluated for varying baseline levels of PCT_FULL. Baseline values of PCT_FULL are chosen in increments of 10 from 100 to 10.

The incremental recreation benefits of increasing PCT_FULL by one unit is calculated in a manner similar to any other facility variable. Predicted visits are calculated using the appropriate district model by setting PCT_FULL equal to its actual level for the period of interest. Starting from its actual level, a value of 1 is then added to each project's observed value of PCT_FULL, and a new visit prediction is obtained analytically.

Estimating the economic benefits of changes in lake levels requires several steps. An example will show how the incremental values of water are computed. We begin with the variable PCT_FULL, defined as the proportion of actual surface acres in a given project in a given year compared to the project's recreational pool. Unadjusted market area visit predictions for Millwood Lake in the Little Rock District are 567,600 for day users and 287,100 for campers. Actual 1985 visits are 905,385 and 683,010 (Table 1). Adjustments are made to the model's constant term to set predicted visits equal to actual visits within the market area. Another term is used to expand from the market area visits to total visits. For day-use predictions, the constant is adjusted by 0.336 (Table 19). This prediction is then increased by a factor of 1/0.877 = 1.14 to expand to the population (Table 10). With both adjustments in place, model predictions are then calculated for varying levels of PCT_FULL.

By choosing PCT_FULL = 90 as an example, the new predictions for visits are 834,600 day users and 629,600 campers. The actual level of PCT_FULL in 1985 was greater than 90, because it was at nearly full recreation pool surface area. This is why predicted visits when PCT_FULL = 90 are less than actual 1985 visits. PCT_FULL is then increased by 1 unit to 91. Using the PCT_FULL elasticity of 1.275 (Appendix C), predicted visits of increasing PCT_FULL by 1 increase to 846,500 total day users and 638,600 total campers (Table 12). The difference in visits at the two values of PCT_FULL are 11,900 day users and 9,000 campers. Using the per-user consumer surpluses given in Table 22 ($2.95 for day use, and $10.40 campers), the incremental benefit of the change in PCT_FULL from 90 to 91 is $35,280 for day users and $93,600 for campers, a total of $128,880. This same process is repeated for various levels of PCT_FULL, from 90, 80, 70, ..., down to 10.

The incremental benefits for increasing the variable PCT_FULL by 1 is of no special interest by itself. However, it is needed for the purpose of converting to benefits per added acre-foot of water. Area capacity relations between surface acres and water volume play an instrumental role in this important conversion. A detailed discussion follows.

Area-capacity regressions were estimated using area-capacity tables for each reservoir. Volume (in acre-feet) was the dependent variable and surface acres the independent variable. Consultation with hydrology faculty at New Mexico State University indicated that such regressions are commonly specified for area capacity relations using higher order polynomial terms of the independent variable. Squared and cubic terms produced models with high explanatory power. No constant term was specified because reservoir volume is zero when surface acres are zero. For this reason, the regression model used to predict reservoir volume as a function of reservoir area is

$$\text{Volume} = (\beta_1 * SA) + (\beta_2 * (SA^2)) + (\beta_3 * (SA^3)) \tag{67}$$

where

SA = surface acres of the reservoir

A regression was estimated for each reservoir in all three districts. About 20 to 30 observations were included in each regression to cover the range of water levels under various management actions and drought conditions. The estimated coefficients by reservoir are presented in Table 28. The high explanatory power of the models produces R-squared values that are all above 0.99.

Surface area and volume both increase as a reservoir is filled. The sensitivity of volume to changes in surface acres is important when translating values per added surface acres into values per added acre-foot. This sensitivity is calculated by differentiating Equation (67) volume (V) surface area with respect to (SA) to get

$$dV/dSA = \beta_1 + (2 * \beta_2 * SA) + (3 * \beta_3 * (SA^2)) \tag{68}$$

The term dV/dSA is related to the slope (steepness) of a reservoir's bank. Steeper bank slopes at the water line have a larger change in volume from a given change in surface area. Even for a given project, the values of dV/dSA often vary considerably according to how full the reservoir is. For bowl shaped reservoirs, 1 acre drawn down takes away less area when full than when near empty.

The numerical value of dV/dSA is calculated for all projects for various levels of surface area from full to empty. For the Millwood Lake example above, the recreation pool surface acres are 29,500. When Millwood is at 90 percent of recreational pool, its surface acres are 29,500 * 0.9 = 26,550. Using the coefficients for Millwood Lake from Table 28, the value of dV/dSA when PCT_FULL = 90 (surface area = 26,550) is

$$dV/dSA = -0.547 + (2 * 0.00028 * 26{,}550) - (3 * (5.78 * 10^{-10}) * (265{,}502) = 13.099 \quad (69)$$

For an increase in PCT_FULL from 90 to 91 percent, a total of [(29,500 * 0.91) - (29,500 * 0.90)] = 295 surface acres is added to the reservoir. The corresponding change in volume is the change in volume with respect to surface acres multiplied by the added surface acres. For Millwood Lake, this translates to

$$(dV/dSA) * (\text{added surface area}) = 13.099 * 295 = 3{,}864 \quad (70)$$

The change in PCT_FULL from 90 to 91 at Millwood is therefore associated with a change in water volume of 3,864 acre-feet.

While the previous discussion is detailed and tedious, it leads to the important calculation of the recreational value of an added acre-foot of water. Because the benefit for a one unit change in PCT_FULL was previously computed as $128,880, the annual value from holding an added acre-foot of water when Millwood Lake is 90 percent of surface area contents is

$$\text{Added Benefit/Ac-Ft/Year} = \$128{,}880/3{,}864 = \$33.35 \quad (71)$$

in 1994 dollars.

This rather lengthy procedure for computing the economic value of an additional acre-foot of water described above is applied to nine values of PCT_FULL of recreation pool surface area for all projects. That is, added water is valued for a wide range of reservoir contents for all study projects.

Results of annual economic benefits per additional acre-foot of water for all study reservoirs are given in Table 29. Results are converted from 1980 to 1994 dollars. The recreational pool surface acres are also given to serve as baselines. In general, the incremental value of management actions that hold an added per acre-foot of water for recreation decreases as a reservoir is drawn down. Also, the values vary across projects with those in the Sacramento District tending to be more constant than the other two districts.

Values presented in Table 29 are annual recreation benefits of management actions; however, managers may be concerned with changing water levels for shorter periods of time. For example, one may seek the benefit of holding additional water one more month. The values in Table 29 can be adjusted to allow such applications. The values of PCT_FULL have been weighed by monthly visitation. Thus, the incremental benefits per acre-foot of water reflect these same proportions. For reference, Table 30 shows the proportion of visitation that occurred in each month from the 1991 NRMS dataset.

This concept is best explained through an example. Suppose a resource manager is considering holding 20,000 more acre-feet of water in Eastman Lake during the single month of May. Data from the 1991 NRMS dataset indicate that 12 percent of visitors came in May (Table 30). Also, suppose the lake is 80 percent full in surface acres. Thus, the appropriate annual marginal value from Table 29 is $10.58. Calculate 12 percent of $10.58 to get a marginal value per acre-foot of water during May of $1.27. The value of the additional 20,000 acre-feet of water during May would then be 20,000 * $1.27 = $25,560. This value could be compared with values of alternative uses of water used for a 1-month period in a cost-benefit analysis framework.

The visitation proportions in Table 30 are from 1991 only. These proportions may have been significantly influenced by the amount of water in each reservoir during each month as well as other factors. Long-term averages would be more accurate than values only from 1991; however, such long-term data on monthly visitation were not available for this study.

One other factor that a recreation manager may wish to consider is that water levels may not influence visitation during some winter months. If the majority of winter visitation is not water-related, then these months should not be considered in calculating monthly marginal values of water. For example, assume in the above example using Eastman Lake that water is not important for recreation during November through March. The visitation proportions in Table 30 would then have to be adjusted to exclude these months. The table shows that 32 percent of annual visitation occurs during these winter months. By excluding the winter months, the remaining proportions would have to be adjusted upward by 1/1 - 0.32 = 1.47. The proportion of visitation occurring in May when the winter months are excluded is now 1.47 * 0.12 = 0.18. A total of 18 percent of nonwinter visitation occurs in May. The incremental benefit of an acre-foot of water during May at 80 percent full is $1.91, about 50 percent higher than the previous example. The value of 20,000 acre-feet of extra water during May is 20,000 * 1.91 = $38,160.

Applications to a Project with Unknown Visitation

This section illustrates by example the estimation of visit levels and benefits for a proposed site within the three districts included in the analysis. Lake Sonoma is located in the Sacramento District about 40 miles north of San Francisco. The dam was completed in 1983, creating a reservoir with a designed recreation pool of 2,700 acres. Surveys were not conducted at Lake Sonoma during the years of the analysis, so the lake was not available for the Sacramento District dataset. USACE records indicate that initial visitation was low as the lake filled, but visitation seemed to stabilize beginning in 1988. The model will be used to predict visitation at Lake Sonoma from 1988 to 1992.

Construction of a database to analyze a new site is similar to the assembly of the initial data. Only information on the independent variables included in the models is necessary to obtain visit predictions. Several important points should be kept in mind in building a database to forecast visitation where actual visitation is unknown.

First, the models are analyzed using travel cost prices measured in 1980 constant dollars. Therefore, any application should convert all monetary values to 1980 dollars. These variables include INCOME (average per capita income) and the wage rate used to estimate the time value of travel. Because all benefit estimates are in 1980 dollars, updating these values to benefits expressed in desired year dollars is required after implementing the forecast.

When using the model to forecast visitation, the independent variables should match the forecast years as closely as possible. Assuming that the structure of the model does not change significantly over time, demographic data should be collected from the census closest to the desired forecast period. For example, the Lake Sonoma application presently described covers the 1988 through 1992 time period, so most demographic data for this application are taken from 1990 census data. County population numbers are updated annually and can match the year of the application exactly. Data on vehicle operation costs also correspond to the application year. Finally, site-level characteristics that vary annually (PCT_FULL and CV) must be adjusted for application to different years. Choosing independent variables that match the forecast year is a separate issue from expressing all monetary values in constant 1980 dollars.

The visit forecast described above is now illustrated by constructing separate day-use and camping databases for the Lake Sonoma applications. The 125-mile market area day-use database contains 13 counties, while the camping data covers 24 counties. The estimated parameters in Table 14 were used to calculate visit predictions for each year. The constant terms are adjusted using the average Sacramento District adjustment factors given in Table 19 (+1.267 for the day-use model and +1.133 for the camping model). The model predicts visitation within the market area. Using the average market area proportions for the Sacramento District (Table 10), the appropriate expansion factors are then used to obtain total predicted visitation. Results are shown in Chapter 5.

Table 31 shows that the model overpredicts total visitation by nearly an order of magnitude at Lake Sonoma. Use of the average constant term adjustment factors over predicts visitation for the Sacramento District.

Per-user benefits were also calculated for Lake Sonoma using the procedure described previously (Chapter 5). Average consumer surplus is $4.48 for day users and $12.37 for campers. These values are plausible compared to the benefits of other Sacramento District sites shown in Table 22. Thus, while the ability of the model to predict visits at a new site in a district may be limited, per-user benefits are likely to be more accurate, because of

offsetting errors. For the log-log model, total benefits and total visits are too high by similar proportions. Dividing total benefits by total visits produces a per-user benefit in which the biases tend to cancel. For this reason, our evidence indicates that predictions of per-user benefits are likely to be acceptable for management decisionmaking at projects where visitation data are poor or missing.

Model Transferability Among Regions

The three districts included in this study represent only a fraction of USACE project operations at the national level. There are 462 USACE projects in 30 districts throughout the United States. However, estimation of travel cost models to study proposed management actions for all projects in all districts is expensive. A national travel cost model transferable to any site would be of considerable value.

In principle, the analysis in this report is applicable to any USACE reservoir project. Parameter estimates obtained from the pooled three district models shown in Table 15 represent the best attempt to use data in all three districts consistently. To justify applying these models to sites outside of the three districts, similar recreation behavior patterns should be evident. While there is no such dataset available at the national level presently, equality of all estimated coefficients across models estimated for each of the three districts would provide one rigorous statistical defense of the transferability of the entire model. A resource manager could then substitute values of the independent variables for a new site into the pooled models. If visitation is known at the site, then the constant term can be adjusted to calibrate the model as described earlier (Chapter 5).

Managers may be interested in how well an RRDM transfers to unstudied districts or regions, because if an RRDM transfers well, managers can save the cost of fitting a new model. For this reason, we conducted statistical tests of the validity of performing model transfers with the data available to us. Statistically, transferring a model from a study region to a target region is valid if all coefficients are equal in both regions.

Transferability of visitation predictions

The best test of the validity of transferring the pooled models to other districts nationally is to estimate travel cost models for other districts in the nation and compare their district predictions against predictions from the pooled model that is applied to the predictor variables in the base district. The coefficients of those base district models could then be tested for equality to the coefficients of the pooled models. The correct test of the hypothesis of coefficient equality for an OLS model is a Chow test (Greene 1993). The test

evaluates whether all coefficients for an estimated model are equal for separate datasets, i.e., whether the structure of the model is equal across datasets.

The method of implementing the Chow test is to estimate separate regression models for each dataset. A single model is estimated over the separate datasets pooled together as a single dataset. We refer to this as the pooled model. The Chow test requires that the independent variables included in all regressions be the same. The test statistic is for model equality across datasets is

$$\text{Chow} = [(ESS_p - ESS_1 - ESS_2)/\text{k}] \;/\; [(ESS_1 + ESS_2) \;/\; (n_1 + n_2 - 2k)] \tag{72}$$

where

ESS_1 and ESS_2 = error sum of squares for regressions using individual datasets

ESS_p = error sum of squares for the pooled model

k = number of independent variables included in the models, including the intercept

n_1 and n_2 = the sample sizes of the two individual datasets

The test statistic has an F-distribution with $(k; n_1 + n_2 - 2k)$ degrees of freedom. If the test statistic is greater than the critical value from an F-distribution table, one rejects the hypothesis of identical parameters and variables (identical models) across datasets.

Unfortunately, travel cost data from other districts are unavailable for this study. However, the data from the three study districts do permit estimation of a pooled model using the data from any two study districts and comparing the results to the model of the third district. This allows a separate test for each of three models in which each is pooled over two districts. In each case, one of the three districts is excluded from the pooled model.

In proceeding with this test, the analyst must first decide which variables to include as visit predictions in the analysis. Because a Chow test rejects the hypothesis of coefficient equality even if only one parameter estimate is significantly different across models, then the hypothesis of coefficient equality is less likely to be rejected if fewer independent variables are included.

One important management application for projects in other districts is to estimate the per-user benefits for individual projects. As total visitation estimates are available for USACE sites, per-user benefits can be multiplied by visitation totals to obtain total benefits. This application would not require that all facility variables be included in the models. Structural equality is first

explored by using only the independent variables most critical to predicting visits of USACE projects:

- POPULATION
- TOT_COST
- SUB_INX
- SUR_ACRES
- PCT_FULL

If Chow tests reject coefficient equality using this limited set of independent variables above, then pooled models with more variables will only increase the probability of rejecting model transferability across districts.

Table 32 presents results of the transferability of several estimated models. Included are each of the individual models, all three combinations of two district models, and a single model with all three districts pooled. Overall, the day-use models have higher explanatory power with all R-squared values above 0.53. The estimated coefficients on TOT_COST in all day-use models suggest highly price-sensitive preferences, (highly negative elasticities) ranging from -4.3 to -2.5. Camping demand is less price-sensitive, with the coefficient on TOT_COST ranging from -2.3 to -0.7. For both day users and campers, Sacramento District demand is the most price-sensitive and Nashville District demand is the least. As explained earlier in the report, Sacramento's high price coefficient can be explained by its abundance of numerous high quality substitutes for USACE reservoirs.

Results of coefficient equality across models are tested with Chow tests. Each test is based on comparing coefficients, using data of any two districts compared against a model fit with data of the remaining district. The fact that independent results are available from regressions estimated for the remaining district permits use of a Chow test. The value of the error sum of squares, ESS_1, is taken from fitting a single model to two districts data; ESS_2 is the error sum of squares taken from a model fit to the remaining individual district model. ESS_p is the error sum of squares from a single model fit using data of all three districts. A total of six Chow tests are conducted, including three models for each possible combination using two-district combinations compared to the remaining one district model. These three tests are performed for both day-use and camping models.

Table 33 presents results of statistical validity tests of the six model transferability exercises. All data needed to perform the tests are in Table 32. The critical F-value for (7,100) degrees of freedom at the 0.95 level is 2.10; all values in Table 33 are much greater than 2.10. Thus, the evidence strongly rejects the hypothesis of model (coefficient) equality across districts for all six tests, i.e., all combinations of two districts predict visits poorly at the remaining district. One explanation of these poor predictions is attributed to the difference between the Sacramento District and the other two districts, especially the presence of abundant strong substitutes in the Sacramento District.

Because of the uniqueness of the Sacramento District, further Chow tests of model transferability were conducted. These tests explored the transferability between only the Little Rock and Nashville Districts. For these tests, separate terms for ESS_1 and ESS_2 are obtained from a Little Rock and Nashville District model. ESS_p came from the pooled Little Rock and Nashville models. Once again, valid transferability is strongly rejected. Results again suggest that coefficient inequality between the Little Rock and Nashville Districts, i.e., models are significantly different.

To repeat, findings indicate that no combination of models estimated on datasets of one or more districts predicts visits as well at the remaining district compared to a model fit specifically for the remaining district.

Transferring benefits/visit to unstudied projects

This section describes how to use the estimated models to transfer average benefits/visits to unstudied projects. Numerous situations occur where managers need to estimate benefits per visit for a reservoir for which there are no current estimates. Per-visit benefits for projects in one of the three study districts can be calculated using the appropriate district models. Benefits per visit for projects outside the three study districts can be estimated by using the three-district generic model. This calculation, illustrated in detail below, involves dividing total benefits by total visits. Both terms are predicted by applying the three-district pooled model to the value of variables at the unstudied project. The result of that exercise produces the following equation for per-user benefits

$$\text{BPER\_VIS} = \frac{-\sum_i [(V_{ij,\max} * P_{\max}) - (V_{ij} * P_{ij})]}{(\beta_{TC}+1) * \sum_i V_{ij}} \tag{73}$$

where

i = county identifier

j = project identifier

$V_{ij,\max}$ = predicted visits at edge of market area

$P_{\max}$ = price to edge of market area (fixed for a project)

V_{ij} = predicted visits from county i to site j

P_{ij} = travel costs for county i to site j

β_{TC} = constant price elasticity coefficient on P_{ij}

Equation 73 is applied by using the visit predictor equation

$$V_{ij} = \beta_0 * P_{ij}^{\beta_{TC}} * \mathrm{FACIL}_j^{\beta_F} * \mathrm{DEMO}_i^{\beta_D} \tag{74}$$

where

β_0 = intercept

DEMO_i = group of county-level variables (demographics and substitutes)

FACIL_j = project variables (facilities, water and fishing quality, etc.)

β_D = constant coefficient estimated for each of the county level variables

β_F = constant coefficient estimated for each of the facility variables

Observe that FACIL_j and β_0 cancel out of Equation 64 to express per-user benefits as the more simplified

$$\mathrm{BPER...VIS} = \frac{-\sum_i [(P_{\max}^{\beta_{TC+1}} * \mathrm{DEMO}_i^{\beta_D}) - (P_{ij}^{\beta_{TC+1}} * \mathrm{DEMO}_i^{B_D})]}{(B_{TC}+1) * \sum_i (P_{ij}^{\beta_{TC}} * \mathrm{DEMO}_i^{\beta_D})} \tag{75}$$

which simplifies some to

$$\mathrm{BPER...VIS} = \frac{-\sum_i [\mathrm{DEMO}_i^{\beta_D}(P_{\max}^{\beta_{TC+1}} - P_{ij}^{\beta_{TC+1}})]}{(\beta_{TC+1}) * \sum_i (P_{ij}^{\beta_{TC}} * \mathrm{DEMO}_i^{\beta_D})}. \tag{76}$$

where the demographic variables, DEMO_i include

$\mathrm{POPULATION}_i$ = population of i^{th} county

INCOME_i = average per capita income of i^{th} county

OCEAN_i = miles to nearest ocean or great lake from the i^{th} county

$\mathrm{MINORITY}_i$ = percentage black and hispanic in the i^{th} county (0 through 100)

$UNEMPLOYMENT_i$ = percentage unemployment in the i^{th} county (0 through 100)

and the price variables include

P_{max} = travel cost to edge of market area, a constant equal to $27.14 for day use and $43.58 for overnight visitors (1980 dollars)

P_{ij} = average travel cost of operating a car from the ith county to the jth project, must be less than $27.14 for day use and less than $43.58 for overnight visitors, (1980 dollars)

Computing the average benefits per visitor at studied projects using Equation 67 requires looking up values for each of the county-level variables for all counties within 175 miles (125 miles for day-use visitors). Values of the variable PMAX are given above and need not be looked up.

For day users, Equation 67 is applied to the estimated parameters for the pooled three-district models (Table 15). The following equation results

$$BPER\_VIS_D = \frac{-\sum_i [(POPULATION_i^{0.989} * INCOME_i^{1.175} * OCEAN_i^{0.463} * \cdots}{-2.352 * \sum_i (P_{ij}^{-3.352} * POPULATION_i^{0.989} * INCOME_i^{1.175} * \cdots} \tag{77}$$

$$\cdots \frac{(MINORITY_i^{-3.649} * UNEMPLOYMENT_i^{-0.649}) * (P_{max}^{-2.352} - P_{ij}^{-2.352})]}{(OCEAN_i^{0.463} * MINORITY_i^{-3.649} * UNEMPLOYMENT_i^{-0.649})]}$$

Equation 77 can be used to estimate benefits per day-use visit at unstudied USACE projects around the country. For the camping model, average benefits per visit for any appropriate large reservoir is similarly calculated with the following equation

$$BPER\_VIS_c = \frac{-\sum_i [(POPULATION_i^{0.735} * INCOME_i^{0.019} * (P_{max}^{-0.681} - P_{ij}^{-0.681})]}{-0.681 * \sum_i (P_{ij}^{-1.681} * POPULATION_i^{0.735} * INCOME_i^{0.019})} \tag{78}$$

Equation 78 can be used to estimate benefits per camper visit at unstudied USACE projects. Performing such a transfer requires developing a dataset on the variables in Equations 77 or 78. While transfers of per-visit benefits can be performed, it is important to know the expected precision of such future efforts.

Results of attempts to transfer estimated per-visit benefits across districts are given in Table 34. A comparison is shown between the per-user benefits using the model estimated for each individual district model and a model applied to that district, but fit originally from the dataset of the other two districts.

Results of attempts to transfer average per-visit benefits are considerably more encouraging than attempting to transfer the whole model. This difference is primarily due to differences in the coefficient on travel costs. Findings are least encouraging for the overnight models and for the Sacramento District. Best transferability occurs when the pooled Nashville-Sacramento model transfers to the Little Rock District, likely because Little Rock facilities are valued by regional residents midway between values of local facilities by Sacramento and Nashville residents. The Sacramento District has many excellent substitutes for USACE facilities, while the Nashville District has few. While not known, results suggest that attempts to transfer per-visit benefits (Equations 77 and 78) to unstudied other districts will be within 100 percent compared to results from conducting a new study tailored to that district.

Additional issues on model transferability

Results discussed in the previous section provide encouragement for future studies that would transfer per-visit benefits across districts. Where per-visit benefits transfer poorly, there may be several factors contributing to the inaccuracy of per-user benefits. For example, the low price elasticity of demand in the Nashville District may not exist in other USACE districts; Nashville's low price elasticity may be due to relatively good regional substitutes not otherwise accounted for in the Nashville model.

Only three districts were included in the analysis of this study. Pooled models using data from more districts with a wider range of variability in the demand predictors would be expected to produce results that better account for recreation behavior at the national level.

Important future work would be a national model constructed with data from numerous USACE districts that represent a wide cross section of conditions around the country. It is unlikely that conditions in the three districts included in this analysis account for the range of variability in all factors affecting national recreation behavior. Wide differences in travel cost coefficients between the Little Rock and Nashville Districts illustrate that geographical proximity does not imply similar recreation behavior.

A footnote to the discussion on the need for added variables is in order. Toward the end of this study, several weeks were spent collecting additional data in which two climate variables were included in the final pooled models presented in Table 15. These variables were average annual cooling degree days and average July humidity. Because of the late stage of the study in which these added data were collected, this contribution to model transferability could not be tested directly. Lacking independent data on benefits at unstudied projects, a resource manager could apply the pooled models to projects in USACE districts nationwide. Because coefficients for the climate variables are estimated using a national database, the impact of these variables are more likely to be accurate at the national level. Additional empirical analysis would further test the potential of transferred models.

Summary of Applications

This section has presented results of the various management questions that can be addressed by models estimated for this study. After calibrating visit predictions at a project to match actual visits, visit predictions can be estimated for management actions that affect facility levels, demographics, and user fees. Per-user recreation benefits per user can be calculated from the models or tables and combined with known visit totals to estimate the total recreation benefit of a site. The change in recreation benefits (consumer surplus) resulting from a wide range of management actions also can be estimated. The three-district pooled models can be applied to USACE projects nationally. Calibration of the constant term sets predicted visits equal to actual visits. Models calibrated using information from additional USACE districts may produce the best overall results.

6 Conclusions

Use of the Regional Recreation Demand Models for Decisionmaking

The eight regional recreation demand models (RRDM's) estimated for this study forecast recreation use and benefits at a target reservoir, even if characteristics of the target reservoir do not perfectly match any exiting study reservoir used to fit the model. These regional models offer several advantages.

First, RRDM's are generalizable to a wide range of management actions, project locations, visitor populations, water levels, and extent of substitute opportunities. By contrast, project-specific models have little generalizability beyond conditions observed at that project.

Next, the RRDM's estimated for this study generalize patterns of observed behavior to a wider range of potential future conditions, including natural conditions such as drought, than is possible with project-specific models. RRDM's also address USACE management actions, such as modifying project operation plans, improving fish habitat, adding facilities, or modifying entrance fees.

Third, RRDM's can be used to estimate benefits resulting from various USACE management actions when events occur outside USACE control. The classic example is stocking fish by a state conservation agency at a USACE project.

Additionally, RRDM's done for this study have a greater potential for accurately transferring predicted benefits to unstudied sites inside or outside the study regions than site specific models. The potential for accurate transfer should be improved especially if measured value of characteristics at the unstudied target sites lies within the range of those at the studied sites.

Fifth, RRDM is superior to a site-specific model, because RRDM bypasses the subjectivity inherent in selecting a similar project at which to apply the model required by site-specific models. This reduction in subjectivity reduces a potentially important source of investigator bias.

Finally, use and benefit predictions at target sites or outside operating conditions at existing study sites are more likely to be accurate than with site-specific models. This greater accuracy is expected because the RRDM's estimated for this study are based on observed behavioral responses to a wide variety of operating conditions, substitute opportunities, and demographic factors at numerous sites throughout several regions.

Summary of Major Findings

In order of importance, findings with the most significant uses for project planning and operations are described below. These include estimates of average benefits per visit, economic values of water for recreation, and values of nonwater facilities.

Average benefits per recreation visit

Average benefits per recreation visit in 1994 dollars range from a high of $6.68 at Lake Isabella in the Sacramento District to a low of $1.87 at Beaver Lake in the Little Rock District for day-use visitors. For overnight visitors, equivalent values range from $30.35 at Lake Barkley in the Nashville District to a low of $7.38 at Lake Kaweah in the Sacramento District. A complete list of these average benefits per visit are summarized in Table 22 for all study projects.

For USACE projects not included in the present study, Equations 77 and 78 present formulas that can be used to estimate average per-visit benefits. Application of the formula requires that data be obtained on several variables for all counties within 175 miles of the reservoir under study. These variables include travel distance from reservoir to county, county population, and the remaining county variables shown in Table 15. Managers can estimate total recreation benefits at the project level when per-visit average benefits described are multiplied by an independent estimate of total visits. Where a percentage breakdown allocation of day-use and overnight visitation is possible, average per-visit benefits can be applied to the estimated total visitation for each of the two classes of use. For application to reservoirs not yet built or for which the present visitation data are unreliable, average per-visit benefits should be multiplied by some independent, reliable estimate of total visitation, best made in conjunction with local experts who are familiar with the geographical area and/or the reservoir.

Economic values of water for recreation

The recreation economic value in 1994 dollars of one additional acre foot of water held for 1 month at a reservoir varies from a high of $52.79 at Lake Millwood in the Little Rock District to a low of $0.27 at Laurel River Lake in the Nashville District. Additional similar results for other projects

can be found by applying annual dollar values in Table 29 in conjunction with monthly visitation percentages in Table 30.

Economic values per acre-foot per month have important management implications in regions where competition for water is strong. These values measure the recreation economic benefits of additional visitors attracted to a reservoir as a consequence of management actions that bring and hold additional water to the reservoir for 1 month. These economic values can be compared directly with economic values of water in competing uses for one month. Examples of competing water uses include flood control, hydropower, irrigation, wildlife habitat, instream flow maintenance, or any other decision where there is a desire to conduct cost-benefit analysis of complex management actions. Details on how the recreational values from additional water are computed are summarized in the text.

As a general principle, recreation values per additional acre foot of water are highest for reservoirs that are closest to population centers and for market areas in which visitors have few water-based recreation substitutes. They are also highest for projects that possess extensive on-site recreational facilities, reservoir banks that have shallow flat slopes at the water level, and for conditions under which water levels are at or near the designed recreation pool.

Economic values of nonwater facilities for recreation

The economic value of installing a single additional unit of recreational facilities varies considerably. It ranges from a high of more than $2.52 million (1994 dollars) for one additional marina at Lake Isabella in the Sacramento District to a low of $54 for one additional parking space at Hensley Lake in the Sacramento District. Additional details are presented in Tables 25a through 25f. These estimated values can be compared to the annualized equivalent cost of installing additional facilities, including the costs of operation and maintenance. This comparison allows managers to conduct cost-benefit analysis of economic effectiveness of installing a wide range of recreation facilities. We are unaware of any study conducted to date that allows managers to scrutinize the economic performance of such a wide range of investments.

As a general principle, additional facilities produce the greatest recreation economic benefit at projects where those facilities are most scarce. Economic values of increasing the number of any class of facility decrease as their number increases. Managers who wish to estimate economic values of other nonwater recreation facilities to unstudied projects should consult the software and user's manual in Ward and Martin (1994).

Scope and Limits of Regional Recreation Demand Model

The RRDM's presented in this report can be used to estimate recreation benefits under actual project conditions. They also can be used to estimate project visitation and benefits under a variety of potential future management actions. However, we attach higher levels of confidence to some uses of these models for management decisions than to others.

The methods of analysis used for this study were designed to obtain good estimates of the important elasticities. By important elasticities, we mean the sensitivity of percentage changes in visitation resulting from a percentage change in site facilities, demographics, or travel costs. The structure of these models is such that the dependent variables is log-transformed. For this reason, they may exhibit large errors in overall visitation predictions. A small error in predicting the logarithm of visits for a large city located close to a project results in large errors in the total visitation predicted for that project.

Adjustment factors presented in Table 19 reflect our attempt to come to terms with this problem. The range of evidence presented in Table 19 does not imply poor performance of these models. These models are designed to estimate sensitivities (elasticities) of factors that affect recreational use significantly. We have every reason to believe that the estimated elasticities are the best available. For the most part, they have the expected algebraic signs and have strong t-statistics.

We have most confidence, therefore, in management applications of these models that require only the estimated elasticities. For the algebraic form of the demand model used, average benefits per day for a given county depend only on the elasticity on travel cost. Therefore, we have higher confidence in our estimate of average benefits per recreation visit.

We are also confident of our estimates of changes in visitation caused by changes in site characteristics even though absolute predicted visitation is often poor. Managers can use the estimated elasticities and calibration factors to adjust predicted visitation to match observed visitation. With these modified predictions, changes in visitation resulting from USACE management actions or from outside forces can be estimated. These estimated effects resulting from management actions can then be multiplied by the per-day values to generate good estimates of the benefits associated with the management actions or of forces outside USACE control. For these reasons, the estimated incremental values for change in facilities and incremental economic values per added acre foot of water should be reliable unless better local data are available.

Local knowledge of visitation patterns can be used to augment this study's regional recreation demand model. Where facilities are used to capacity constantly, the benefits from building new facilities will likely exceed those

predicted by the model. Where local knowledge shows that facilities go unused most of the time, the model may overpredict benefits from new facilities. If existing picnic tables go unused, it makes little economic sense to build more, regardless of what the recreation demand model predicts.

Similarly, the confidence of the model's predicted decrease in visitation is due to increases in entrance fees. A resource manager can use estimates of current visitation in conjunction with our estimated elasticity on travel cost to estimate the consequences of various entrance fees on future visitation.

When site characteristics, water levels, and demographics take on values outside the range that existed in the data used to fit the models, visits predicted by the model will be less accurate. Problems associated with out-of-range projections were demonstrated in both the short- and long-term projections for the Sacramento District. Data used to estimate the Sacramento model were all collected during drought years. Projections for the wet year of 1993 produced considerable over-estimates of actual visitation for several reservoirs hardest hit by the 1983 through 1985 droughts.

Our confidence in visitation projections also decreases as time moves farther away from the 1983 through 1986 period for which the model was estimated. The long-term projections for the Nashville District failed to predict large increases in visitation that occurred in the relatively short time between 1985 and 1990. Because the model was estimated using data from only a few years, the model cannot track trends in visitation caused by changing visitor preferences for water-based recreation.

Finally, there is less confidence in using the models to predict visitation at an existing nonstudy project or at a proposed project. Analysis of visitation at Sonoma Lake demonstrates these models perform poorly at predicting total visitation, even for a project located within one of the three studied districts. Use of the pooled three-district model to predict visitation at a site outside the three study districts could be off by an order of magnitude. Use of the pooled model to predict visitation at a proposed project or at a project outside the three districts should be accompanied by a calibration exercise in which visit predictors are calibrated against independent reliable estimates of visitation. After the model is calibrated in this manner, it can be used with more confidence to assess the consequences of various potential management actions.

While the model may be unable to predict visitation reliably at an unstudied or proposed reservoir, our evidence indicates that the models can provide an accurate estimate of per-visit benefits, particularly if the unstudied reservoir is located within one of the three districts studied. Errors associated with using the pooled model to calculate per-visit benefits for sites within the three districts studied were typically bounded by a factor of 0.5 to 2.0. Knowledge of per-visit benefits is of most practical use if combined with an independent estimate of total visitation. If unavailable, estimated benefits per visit should be multiplied by total visits predicted by the models.

An additional finding of this study is that recreation behavior differs across districts in ways that cannot be explained from differences in the measurable site characteristics, travel costs, availability of substitutes, or demographics used in these models. Chow tests rejected the null hypothesis that model parameters are equal across regions. These differences in behavior may be due to cultural differences or to differences in the availability of substitute recreation opportunities that are not water-based.

Future Work Needed with Management Implications

Data improvements

Visitor surveys are most useful for demand modeling when they represent random samples of all project visitors. When budget and time permit, sampling is done profitably at a variety of project access points, so the resulting data are not skewed toward one part of the project. Effort should also be made to include visitors who do not pass through official access points.

It is important that demand models be estimated with data from projects that have a wide range of site characteristics. For example, all of the Sacramento data were collected in drought years. Using the model estimated from those years to project to nondrought years resulted in poor model performance. Data on visitation in both drought and nondrought years would allow better modeling of the influence of lake levels on visitation across a wider range of conditions.

It is important that visitor surveys determine whether the visit is part of a single- or multiple-purpose trip. If a visitor's trip is for several purposes, visitors should be asked if the project was the primary purpose of the trip. The travel cost approach is not designed to estimate demand and benefits for multipurpose visitors. The approach taken in this study to exclude multiple purpose trips by limiting the market area was necessary but imprecise.

Finally, investigations of the importance of demographics on visitation will be difficult as long as county averages or totals are the units of visitor observations. A household survey of recreation behavior would measure differences in visitation rates better among different age/income/ethnic groups and allow more refined measurement of travel costs and availability of substitutes. Visitation data that exclude visitor characteristics other than home zip code will allow only the less precise zonal travel cost modeling.

Identification of pilot projects

Recreation preferences and the influence of temporary demand shifters can be tracked by surveying visitors continually for at least some projects over a

period of many years. Visitation data at the sampled sites showed large fluctuations from year to year. Without long-term records on visitation at a single project, one cannot determine the causes of these fluctuations, and therefore cannot project visitation into future years with confidence.

Integrated hydrological, biological, and economic models

Evaluating the economic consequences of management actions requires an interdisciplinary effort to understand the complex interrelationships between physical conditions, biological factors, and human perceptions and behaviors (Hansen and Badger 1991). Most studies that estimate recreation economic values, including the present one, concentrate on modeling this latter human behavioral component. Few have attempted to operationalize the entire cause and effect relationship that links interrelated hydraulic, biological, and behavioral models. The study by Cole et al. (1990), that describes the development of RIOFISH, is one exception. RIOFISH is an integrated interdisciplinary planning model for conducting cost-benefit analysis of fishing management actions in New Mexico. An interdisciplinary model would provide even more benefits than the regional recreation demand model reported in this study.

An interdisciplinary model would provide greater flexibility in formulating and evaluating effects of various water management plans, because an interdisciplinary model can incorporate hydrological or biological management decisions made to mitigate the effects of water management on fisheries and related ecological indicators of performance. Such incorporation gives a more complete picture of the benefits and costs involved. The simple estimator of the morphoedaphic index used for the present regional recreation demand model responds only to changes in reservoir depth and total dissolved solids and ignores stocking, regulations, and habitat management.

In addition, an interdisciplinary model would provide a much improved estimator of interactions between management actions, the resource, and resource users, including interactions between stocking, regulations, fish species introductions, habitat management, access, boat ramps, campsites, picnic tables, and the like.

Moreover, the interdisciplinary approach integrates over the entire river basin and accounts for hydrologic interactions among numerous reservoirs. Interdisciplinary models are the only known way to develop a comprehensive, conceptually correct accounting of upstream-downstream interactions of modified project operation plans. Such basin-wide effects of project management actions are especially important in periods of drought for formulating economically beneficial management plans. The drought in the Missouri Basin in the early 1990's illustrates an example.

Finally, an interdisciplinary model would augment fisheries and other biological data currently collected by USACE. An interdisciplinary model would estimate the effects of water-level fluctuations on fish recruitment and

yield and allow managers to modify the water-fluctuation coefficient as information improves. Especially where water exchange rates and water-level fluctuations are considerable and where there is interaction with various management decisions, the interdisciplinary approach provides a resource to decisionmakers who wish to manage proactively.

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Table 1
Estimated Total Visits for Included Sites

Site Name	Year	Day-Use Visits	Camper Visits
a. Little Rock District (Surveyed in 1985 only)			
Beaver Lake	1985	3,521,856	435,286
Blue Mountain Lake	1985	289,528	32,170
Bull Shoals Lake	1985	3,450,233	181,591
Lake Dardanelle	1985	3,014,646	334,961
Millwood Lake	1985	905,385	683,010
Nimrod Lake	1985	434,173	48,241
Norfork Lake	1985	2,985,276	331,697
Table Rock Lake	1985	4,033,222	826,082
b. Nashville District			
Center Hill Lake	1985	3,371,806	459,792
Center Hill Lake	1986	3,581,590	583,049
Cheatham Lake	1985	1,406,774	43,508
Cheatham Lake	1986	1,933,117	59,787
Cordell Hull Lake	1985	1,873,683	162,929
Cordell Hull Lake	1986	2,095,262	182,197
Dale Hollow Lake	1985	1,584,969	679,272
Dale Hollow Lake	1986	1,513,107	648,474
J. Percy Priest Lake	1984	5,017,934	209,081
J. Percy Priest Lake	1985	7,327,783	226,632
Lake Barkley	1986	4,741,088	412,268
Lake Cumberland	1983	3,927,828	485,462
Laurel River Lake	1985	120,300	0[1]
c. Sacramento District			
Black Butte Lake	1983	277,543	34,303
Black Butte Lake	1984	252,627	31,224
Black Butte Lake	1985	235,093	29,056
Eastman Lake	1983	103,278	38,199
Eastman Lake	1984	86,109	31,848
Eastman Lake	1985	74,838	27,680
Englebright Lake	1983	103,702	34,567

[1] Laurel River Lake lacks camping facilities.

(Continued)

Table 1 (Concluded)			
Site Name	**Year**	**Day-Use Visits**	**Camping Visits**
Hensley Lake	1983	39,237	64,018
Hensley Lake	1984	41,472	67,666
Hensley Lake	1985	35,893	58,562
Lake Isabella	1983	1,385,381	346,345
Lake Isabella	1984	1,285,474	321,369
Lake Isabella	1985	1,356,392	339,098
Lake Kaweah	1983	747,765	39,356
Lake Kaweah	1985	578,334	30,439
Lake Mendocino	1983	1,209,141	230,313
Lake Mendocino	1984	1,155,205	220,239
Lake Mendocino	1985	1,120,479	213,424
New Hogan Lake	1983	270,911	85,551
New Hogan Lake	1984	321,382	101,489
New Hogan Lake	1985	321,778	101,614
Pine Flat Lake	1983	724,450	108,251
Pine Flat Lake	1984	567,602	84,814
Pine Flat Lake	1985	614,554	91,830
Success Lake	1983	605,323	59,867
Success Lake	1984	567,107	56,088
Success Lake	1985	613,466	60,672

Table 2
USACE Sites Included in Analysis and Years Surveyed

Site Name	1983	1984	1985	1986
Little Rock District				
Beaver Lake			XX	
Blue Mountain Lake			XX	
Bull Shoals Lake			XX	
Lake Dardanelle			XX	
Millwood Lake			XX	
Nimrod Lake			XX	
Norfork Lake			XX	
Table Rock Lake			XX	
Nashville District				
Center Hill Lake			XX	XX
Cheatham Lake			XX	XX
Cordell Hull			XX	XX
Dale Hollow Lake			XX	XX
J. Percy Priest Lake		XX	XX	
Lake Barkley				XX
Lake Cumberland	XX			
Laurel River Lake			XX	
Sacramento District				
Black Butte Lake	XX	XX	XX	
Eastman Lake	XX	XX	XX	
Englebright Lake	XX			
Hensley Lake	XX	XX	XX	
Lake Isabella	XX	XX	XX	
Lake Kaweah	XX		XX	
Lake Mendocino	XX	XX	XX	
New Hogan Lake	XX	XX	XX	
Pine Flat Lake	XX	XX	XX	
Success Lake	XX	XX	XX	

Note: An XX indicates the site was surveyed that year.

Table 3
U.S. Consumer Price Levels
1980-1994; 1980 = 1.00

Year	Level Compared to 1980
1980	1.00
1981	1.10
1982	1.17
1983	1.20
1984	1.26
1985	1.30
1986	1.33
1987	1.37
1988	1.43
1989	1.50
1990	1.58
1991	1.65
1992	1.70
1993	1.75
1994	1.80

Note: Any dollar value in this study, such as average benefits per visit, can be multiplied by the tabled year's entry to update from 1980 values to the desired year. Source: Federal Reserve Bank of St. Louis (1995).

Table 4
List of Independent Variables

1. $POPULATION_{ik}$	The population of county *i* during year *k*, taken from the USA Counties database
2. $UNEMPLOYMENT_{i,1980}$	The percentage unemployment rate of county *i* from the 1980 census
3. $INCOME_{i,1980}$	The average annual income in county *i* from the 1980 census
4. $UNDER\_18_{i,1980}$	The percent of individuals in county *i* under 18 years of age, taken from the 1980 census
5. $OVER\_65_{i,1980}$	The percent of individuals in county *i* over 65 years of age, taken from the 1980 census
6. $MEDIAN\_AGE_{i,1980}$	The median age in county *i* from the 1980 census
7. $WAGE\_RATE_{i,1980}$	The per capita wage rate of those in the work force in county *i*, from the 1980 census
8. $BLACK_{i,1980}$	The percentage of black individuals in county *i* from the 1980 census
9. $HISPANIC_{i,1980}$	The percent of hispanic individuals in county *i* from the 1980 census
10. $MINORITY_{i,1980}$	The sum of black and hispanic individuals in county *i* from the 1980 census (used to avoid multicollinearity between the two variables)
11. $PICNIC_j$	The number of day-use picnic tables at site *j*
12. $PARKING_j$	The number of parking spaces at site *j* (the sum of car and trailer spaces)
13. $LANES_j$	The number of boat launch lanes at site *j*
14. $CAMPS_j$	The number of camping sites at site *j*
15. $BEACHES_j$	The number of swimming beaches at site *j*
16. $MARINAS_j$	The number of full-service marinas at site *j*
17. $DOCKS_j$	The number of private boat docks at site *j*
18. $SPECIES_j$	The number of game fish species existing in reservoir *j*
19. $BASS_j$	A 1 if bass are present in reservoir *j*, a_n0 otherwise
20. $TROUT_j$	A 1 if trout are present in reservoir *j*, a_n0 otherwise
21. $STOCKING_{jk}$	The number of catchable fish from stocking at reservoir *j* in year *k*
22. MEI_{jk}	The morphoedaphic index of reservoir *j* in year *k*
23. $SECCHI_{jk}$	The average (in feet) of all secchi readings at reservoir *j* in year *k*
24. TDS_{jk}	The average (in mg per liter) of all total dissolved solid readings at reservoir *j* in year *k*

(Continued)

Table 4 (Concluded)	
25. SUR_ACRES_j	The surface acres of site *j* at the recreation pool level
26. PCT_FULL_{jk}	The average percentage of recreation pool surface acres for site *j* during year *k*, equal to 100 if the site averaged more than recreation pool level
27. CV_{jk}	The coefficient of variation for monthly average surface acres of site *j* during the recreation season for year *k*
28. $SHORE_j$	The recreation pool shore miles of site *j*
29. TOT_COST_{ijk}	The total per-visitor round-trip travel cost (travel plus time) from county *i* to site *j* during year *k*
30. SUB_INDEX_{ij}	The substitute index of alternative lake or reservoir recreation to site *j* for county *i*
31. $OCEAN_i$	The one-way distance from county *i* to the nearest ocean or Great Lake recreation site

Table 5
Mean Value of Independent Variables by District

Variable Name	Varies by	Little Rock District Mean	Nashville District Mean	Sacramento District Mean
POPULATION (#)	County	34,927	38,325	327,727
UNEMPLOYMENT (Percent)	County	7.48	9.00	9.49
INCOME (1980 $/year)	County	9,171	9,062	12,898
UNDER-18 (%)	County	27.13	28.59	25.43
OVER-65 (%)	County	15.30	12.25	10.12
MEDIAN-AGE (year)	County	33.58	30.83	30.34
WAGE-RATE (1980 $/hour)	County	6.19	6.62	8.04
BLACK (%)	County	5.64	5.57	3.35
HISPANIC (%)	County	0.74	0.72	14.41
MINORITY (%)	County	6.36	6.30	17.76
PICNIC (#)	Project	57.60	288.19	81.36
PARKING (#)	Project	2,559.46	4,138.64	755.28
LANES (#)	Project	93.74	70.16	8.27
CAMPS (#)	Project	607.48	583.95	244.89
BEACHES (#)	Project	8.92	7.75	1.24
MARINAS (#)	Project	6.30	6.04	1.22
DOCKS (#)	Project	187.72	78.62	0.00
SPECIES (#)	Project	7.71	7.86	5.44
BASS (1=Yes, 2=No)	Project	1.00	1.00	1.00
TROUT (1=Yes, 2=No)	Project	0.25	0.50	0.80
STOCKING (#)	Project	69,126	16,298	24,010
MEI (#)	Project	2.49	2.47	2.69
SECCHI (feet)	Project	7.65	7.86	9.43
TDS (mg/l)	Project	93.68	119.57	175.05
REC-SA (acres)	Project	29,279	20,671	2,501
PCT-FULL (%)	Project	99.33	95.98	90.18
CV (#)	Project	11.28	4.13	17.05
SHORE (miles)	Project	370.12	481.06	28.59
TOT-COST (1980 $)	Project-County	14.69	15.13	17.01
SUB-INDEX (#)	County	14,673	12,426	5,751
OCEAN (miles)	County	493.8	396.8	113.0

Table 6
Percentage of Total Sampled Visitors Originating from Various One-Way Distances - Average of Little Rock, Nashville, and Sacramento Districts

Mileage Range	Percent of Sampled Day Users	Percent of Sampled Campers
> 250 Miles	10.7%	17.2%
225-250 Miles	+ 1.1%	+ 2.8%
200-225 Miles	+ 1.6%	+ 4.1%
175-200 Miles	+ 1.0%	+ 2.6%
150-175 Miles	+ 2.9%	+ 8.7%
125-150 Miles	+ 1.0%	+ 3.8%
100-125 Miles	+ 1.6%	+ 4.8%
< 100 Miles	80.0%	55.9%

Table 7
Sample Observation Size of Number of Counties for Single District Models with Different Defined Market Areas

Market Area Radius	Sample Observations
a. Little Rock District	
100 Miles	189
125 Miles	307
150 Miles	444
175 Miles	616
200 Miles	795
225 Miles	1,011
250 Miles	1,261
b. Nashville District	
100 Miles	623
125 Miles	993
150 Miles	1,387
175 Miles	1,755
200 Miles	2,439
225 Miles	3,026
250 Miles	3,758
c. Sacramento District	
100 Miles	169
125 Miles	264
150 Miles	348
175 Miles	462
200 Miles	617
225 Miles	737
250 Miles	859

Table 8
Percentage of Counties with Zero Sampled Visits for Different Market Areas - Average Across Little Rock, Nashville, and Sacramento Districts

Market Area Radius	Percent of Counties with Zero Sampled Day-Use Visits	Percent of Counties with Zero Sampled Camper Visits
100 Miles	32.2	51.4
125 Miles	41.1	59.3
150 Miles	47.0	64.6
175 Miles	51.7	68.5
200 Miles	56.7	72.6
225 Miles	59.2	75.1
250 Miles	62.1	77.3

Table 9
Percentage of Visitation Explained by Models R^2 of Basic Regression Model with Different Defined Market Areas

Market Area Radius	Day-Use Model	Camping Model
100 Miles	0.61	0.58
125 Miles	0.60	0.58
150 Miles	0.58	0.57
175 Miles	0.57	0.55
200 Miles	0.56	0.55
225 Miles	0.54	0.53
250 Miles	0.54	0.53

Table 10
Proportion of Sampled Visitors within Defined Market Areas, by Project

Site	Day-Use Proportion	Camping Proportion
Little Rock District	**0.755**	**0.708**
Beaver Lake	0.772	0.689
Blue Mountain Lake	0.750	0.810
Bull Shoals Lake	0.563	0.408
Lake Dardanelle	0.900	0.785
Millwood Lake	0.877	0.937
Nimrod Lake	0.876	0.839
Norfork Lake	0.710	0.662
Table Rock Lake	0.589	0.530
Nashville District	**0.938**	**0.754**
Center Hill Lake	0.956	0.892
Cheatham Lake	0.982	0.983
Cordell Hull Lake	0.975	0.900
Dale Hollow Lake	0.897	0.333
J. Percy Priest Lake	0.977	0.800
Lake Barkley	0.888	0.628
Lake Cumberland	0.884	0.742
Laurel River Lake	0.942	---
Sacramento District	**0.847**	**0.813**
Black Butte Lake	0.877	0.802
Eastman Lake	0.729	0.799
Englebright Lake	0.908	0.955
Hensley Lake	0.886	0.766
Lake Isabella	0.657	0.789
Lake Kaweah	0.842	0.733
Lake Mendocino	0.871	0.907
New Hogan Lake	0.952	0.922
Pine Flat Lake	0.833	0.623
Success Lake	0.914	0.833

Table 11
Correlation Coefficients for Site Facility Variables (Data Include All Three Districts)

Variable	REC_SA	PARKING	CAMPS	PICNIC	LANES	BEACHES	MARINAS	DOCKS
REC_SA	1.00	0.59	0.73	0.40	0.60	0.56	0.72	0.75
PARKING		1.00	0.81	0.80	0.71	0.73	0.68	0.38
CAMPS			1.00	0.44	0.76	0.78	0.86	0.45
PICNIC				1.00	0.27	0.40	0.27	0.22
LANES					1.00	0.80	0.72	0.65
BEACHES						1.00	0.70	0.48
MARINAS							1.00	0.41
DOCKS								1.00

Table 12
Regression Results - Little Rock District

Variables	Varies by	Day-Use Model		Camping Model	
		Coefficient	T-statistic	Coefficient	T-statistic
Intercept		0.240	(0.030)	11.611	(1.892)
POPULATION	County	1.337	(9.151)	0.775	(8.469)
TOT_COST	County-Project	-3.543	(-19.296)	-1.929	(-15.734)
INCOME	County	1.257	(1.649)	0.468	(1.039)
SUB_INDEX	County	-2.811	(-4.751)	-0.366	(-0.932)
SUR_ACRES	County	0.107	(6.587)[1]	0.281	(8.659)[1]
LANES	Project	0.084	(4.637)[1]	0.020	(1.078)[1]
BEACHES	Project	0.071	(4.009)[1]	0.062	(3.465)[1]
MARINAS	Project	0.143	(6.913)[1]	0.131	(3.862)[1]
DOCKS	Project	0.056	(7.689)[1]	0.050	(3.777)[1]
PARKING	Project	0.169	(6.842)[1]		
PICNIC	Project	0.082	(4.679)[1]		
CAMPS	Project			0.219	(6.010)[1]
UNDER_18	County	2.163	(2.086)		
SPECIES	Project	0.719	(2.590)		
MINORITY	County			0.235	(0.287)
CV	Project			-0.741	(-6.254)
TDS	Project			-0.973	(-6.152)
OCEAN	County			-2.210	(-5.198)
PCT_FULL	Project	1.275[2]		1.275[2]	
Observations		307		616	
R-Square of Model		0.672		0.515	
F-Value of Model		87.365		71.387	

[1] Facility variable estimated using the facility index approach discussed in Chapter 4. T-statistics are from first-stage models and are likely inflated.
[2] PCT_FULL coefficient estimated with supplemental data. See Appendix C for explanation.

Table 13
Regression Results - Nashville District

Variable	Varies by	Day-Use Model Coefficient	Day-Use Model T-statistic	Camping Model Coefficient	Camping Model T-statistic
Intercept		-11.826	(3.374)	-2.272	(1.156)
POPULATION	County	0.645	(10.113)	0.318	(9.675)
TOT_COST	County-Project	-2.481	(-26.596)	-0.743	(-14.819)
INCOME	County	1.654	(6.227)	0.321	(2.127)
SUB_INDEX	County	-1.557	(-6.101)	-0.499	(-4.631)
SUR_ACRES	Project	0.243	(19.391)[1]	0.265	(17.026)[1]
LANES	Project	0.136	(20.552)[1]	0.367	(18.528)[1]
BEACHES	Project	0.15	(14.652)[1]	0.127	(9.895)[1]
MARINAS	Project	0.285	(16.742)[1]	0.265	(14.197)[1]
DOCKS	Project	0.027	(6.385)[1]	0.017	(4.637)[1]
PARKING	Project	0.163	(20.962)[1]		
PICNIC	Project	0.192	(21.225)[1]		
CAMPS	Project			0.263	(15.468)[1]
OVER_65	County	-0.513	(-2.359)		
OCEAN	County	1.155	(2.968)		
MINORITY	County	-1.005	(-1.448)	-0.258	(-0.758)
MEI	Project	0.519	(7.281)	0.798	(8.099)
CV	Project			-1.016	(-8.800)
TDS	Project			-0.529	(12.071)
PCT_FULL	Project	1.275[2]		1.275[2]	
Observations		993		1,755	
R-Square of Model		0.623		0.350	
F-Value of Model		180.740		104.376	

[1] Facility variable estimated using the facility index approach discussed in Chapter 4. T-statistics are from first-stage models and are likely inflated.
[2] PCT_FULL coefficient estimated with supplemental data. See Appendix C for explanation.

Table 14
Regression Results - Sacramento District

Variable	Varies By	Day-Use Model Coefficient	Day-Use Model T-statistic	Camping Model Coefficient	Camping Model T-statistic
Intercept		6.956	(0.594)	-5.088	(-0.875)
POPULATION	County	1.001	(8.578)	0.875	(12.891)
TOT_COST	County-Project	-4.290	(-16.816)	-2.334	(-15.207)
INCOME	County	-0.513	(-0.472)	0.640	(1.149)
SUB_INDEX	County	-0.234	(-0.413)	-0.960	(-2.609)
SUR_ACRES	Project	0.410	(5.092)[1]	0.071	(1.318)[1]
LANES	Project	0.933	(7.109)[1]	0.623	(7.400)[1]
BEACHES	Project	0.009	(0.074)[1]	0.344	(4.399)[1]
MARINAS	Project	0.282	(1.433)[1]	0.881	(7.190)[1]
PARKING	Project	0.243	(2.720)[1]		
PICNIC	Project	0.160	(2.275)[1]		
CAMPS	Project			0.228	(4.760)[1]
PCT_FULL	Project	1.103[2]	(4.349)	1.103[2]	
UNEMPLOYMENT	County	-1.885	(-2.550)		
CV	Project	-0.532	(-3.442)	-0.126	(-1.213)
MEI	Project			0.195	(1.248)
OCEAN	County			0.217	(1.520)
Observations		264		462	
R-Square of Model		0.624		0.543	
F-Value of Model		60.589		67.193	

[1] Facility variable estimated using the facility index approach discussed in Chapter 4. T-statistics are from first-stage models and are likely inflated.
[2] PCT_FULL coefficient estimated with supplemental data. See Appendix C for explanation.

Table 15
Regression Results - Three-District Pooled Model

Variable	Varies By	Day-Use Model		Camping Model	
		Coefficient	T-statistic	Coefficient	T-statistic
Intercept		-10.151	(-2.465)	-2.951	(-1.589)
POPULATION	County	0.989	(18.580)	0.735	(24.247)
TOT_COST	County-Project	-3.352	(-36.681)	-1.681	(-30.320)
INCOME	County	1.175	(3.221)	0.019	(0.110)
SUB_INDEX	County	-1.539	(-8.487)	-1.088	(-10.809)
SUR_ACRES	Project	0.396	(12.848)[1]	0.426	(19.231)[1]
LANES	Project	0.258	(13.243)[1]	0.344	(16.542)[1]
BEACHES	Project	0.149	(6.860)[1]	0.110	(6.524)[1]
MARINAS	Project	0.353	(8.667)[1]	0.476	(13.894)[1]
DOCKS	Project	0.062	(6.573)[1]	0.007	(0.923)[1]
PARKING	Project	0.280	(10.908)[1]		
PICNIC	Project	0.063	(3.362)[1]		
CAMPS	Project			0.268	(13.997)[1]
CV	Project	-0.330	(-4.972)	-0.631	(-15.493)
SHORE	Project	-0.822	(-8.727)	-0.894	(-16.584)
SPECIES	Project	0.976	(4.719)	1.428	(11.851)
MEI	Project	0.233	(2.782)	0.702	(10.686)
OCEAN	County	0.463	(3.424)		
MINORITY	County	-3.649	(-5.582)		
UNEMPLOYMENT	County	-0.649	(-3.131)		
TDS	Project			-0.538	(-8.500)
PCT_FULL	Project	1.152[2]		1.152[2]	
COOLING_DD	Project	0.4668[2]		0.4668[2]	
JULY_HUMIDITY	Project	1.0877[2]		1.0877[2]	
Observations		1,564		2,833	
R-Square of Model		0.593		0.465	
F-Value of Model		188.458		245.577	

[1] Facility variable estimated using the facility index approach discussed in Chapter 4. T-statistics are from first-stage models and are likely inflated.
[2] PCT_FULL and climate coefficients estimated with supplemental data. See Appendices C and D for explanation.

Table 16
Unadjusted Site Visitation Predictions Using Individual District Models

Site	Day-Use Prediction	Camping Prediction
Little Rock District		
Beaver Lake	10,323,000	89,500
Blue Mountain Lake	42,500	4,900
Bull Shoals Lake	3,182,600	71,000
Lake Dardanelle	935,900	151,900
Millwood Lake	567,600	287,100
Nimrod Lake	124,300	20,500
Norfork Lake	1,710,400	31,400
Table Rock Lake	3,422,970	143,400
Nashville District		
Center Hill Lake	737,000	202,100
Cheatham Lake	1,553,800	113,900
Cordell Hull Lake	629,100	124,300
Dale Hollow Lake	632,200	365,300
J. Percy Priest Lake	1,816,200	294,600
Lake Barkley	1,219,000	255,300
Lake Cumberland	735,500	197,100
Laurel River Lake	29,300	---
Sacramento District		
Black Butte Lake	298,900	51,700
Eastman Lake	101,400	34,500
Englebright Lake	81,700	13,000
Hensley Lake	312,800	60,900
Lake Isabella	218,100	103,100
Lake Kaweah	256,200	29,500
Lake Mendocino	2,873,200	241,800
New Hogan Lake	760,500	103,400
Pine Flat Lake	4,188,900	167,700
Success Lake	151,200	21,600

Table 17
Long-Range Sacramento District Forecasts Originating in 1985 for 1986-1993 (Percent error of predictions in parentheses)

Year	Actual Day-Use Visits	Predicted Day-Use Visits	Actual Camping Visits	Predicted Camping Visits
a. Black Butte Lake				
1986	284,800	228,200 (-20)	34,800	32,400 (-7)
1987	185,900	221,700 (+19)	22,700	30,100 (+33)
1988	221,800	276,300 (+25)	27,100	30,400 (+12)
1989	248,700	280,000 (+13)	30,400	27,800 (-9)
1990	236,200	254,300 (+8)	28,900	29,200 (+1)
1991	246,200	210,600 (-14)	30,100	33,200 (+10)
1992	291,200	312,600 (+7)	35,600	41,700 (+17)
1993	275,200	313,700 (+14)	33,600	43,200 (+29)
b. Eastman Lake				
1986	94,600	193,700 (+105)	34,900	50,000 (+43)
1987	90,500	166,000 (+83)	33,400	47,800 (+43)
1988	74,400	113,700 (+53)	27,500	35,100 (+27)
1989	44,300	107,000 (+142)	16,300	38,900 (+139)
1990	31,400	120,300 (+283)	11,600	26,400 (+128)
1991	31,300	83,800 (+168)	11,600	8,000 (+141)
1992	48,700	113,700 (+133)	8,000	34,100 (+89)
1993	60,300	334,100 (+454)	22,300	62,900 (+182)
c. Hensley Lake				
1986	35,700	88,300 (+147)	58,600	114,600 (+96)
1987	36,000	46,100 (+28)	59,100	66,800 (+13)
1988	32,300	45,700 (+41)	52,900	59,700 (+13)
1989	33,100	37,600 (+14)	54,300	57,200 (+5)
1990	39,400	33,800 (-14)	64,700	46,700 (-28)
1991	44,100	35,600 (-19)	72,300	62,100 (-14)
1992	47,100	41,500 (-12)	77,400	65,200 (-16)
1993	43,200	128,700 (+198)	70,900	144,400 (+104)
d. Lake Kaweah				
1986	596,400	961,100 (+61)	31,800	38,000 (+19)
1987	599,100	745,600 (+24)	32,000	33,700 (+5)
1988	657,600	689,400 (+5)	35,100	33,100 (-6)
1989	517,600	701,800 (+36)	27,700	34,200 (+23)
1990	671,400	677,500 (+1)	35,800	31,100 (-13)
1991	654,200	729,500 (+12)	34,900	36,500 (+5)
1992	695,800	557,200 (-20)	37,100	27,500 (-26)
1993	603,500	801,800 (+33)	32,200	40,100 (+25)

(Continued)

Table 17 (Concluded)				
Year	Actual Day-Use Visits	Predicted Day-Use Visits	Actual Camping Visits	Predicted Camping Visits
e. Lake Mendocino				
1986	1,148,200	1,019,900 (-11)	219,900	243,800 (+11)
1987	1,150,300	908,800 (-21)	220,300	219,400 (0)
1988	1,032,800	1,204,800 (+17)	197,800	236,100 (+19)
1989	1,049,900	1,432,500 (+36)	201,000	259,100 (+29)
1990	1,150,100	1,718,600 (+49)	220,200	275,500 (+25)
1991	1,083,000	1,631,900 (+51)	207,400	264,500 (+28)
1992	1,084,900	1,349,100 (+24)	207,700	264,400 (+27)
1993	1,087,300	2,026,200 (+86)	208,200	300,000 (+44)
f. New Hogan Lake				
1986	367,000	554,200 (+51)	114,900	139,700 (+22)
1987	325,600	267,100 (-18)	101,900	91,700 (-10)
1988	235,000	113,100 (-52)	73,600	46,200 (-37)
1989	190,400	133,800 (-30)	59,600	43,800 (-27)
1990	215,200	148,800 (-31)	67,400	48,700 (-28)
1991	225,300	130,500 (-42)	70,500	52,000 (-26)
1992	206,100	177,300 (-14)	64,500	63,700 (-1)
1993	362,200	604,500 (+67)	113,400	158,700 (+40)
g. Pine Flat Lake				
1986	656,900	1,523,900 (+132)	100,000	148,500 (+49)
1987	546,500	592,600 (+8)	83,200	93,200 (+12)
1988	435,900	397,300 (-9)	66,300	62,600 (-6)
1989	357,200	323,400 (-9)	54,400	54,400 (0)
1990	364,900	307,700 (-16)	55,500	52,500 (-5)
1991	399,200	326,200 (-18)	60,700	57,300 (-6)
1992	366,900	348,900 (-5)	55,800	57,400 (+3)
1993	540,300	1,214,200 (+124)	82,200	142,900 (+74)
h. Success Lake				
1986	661,200	1,316,800 (+99)	68,500	113,300 (+65)
1987	583,600	522,500 (-10)	60,500	48,700 (-20)
1988	550,400	552,500 (0)	57,000	43,000 (-25)
1989	543,700	692,900 (+27)	56,400	61,100 (+8)
1990	550,000	536,500 (-2)	57,000	42,800 (-25)
1991	607,500	652,400 (+7)	63,000	62,500 (-1)
1992	567,800	543,400 (-4)	58,800	48,400 (-18)
1993	542,700	1,215,900 (+124)	56,200	96,600 (+72)

Table 18
Short-Range Sacramento District Forecasts, Predicted Visits Adjusted Annually for 1986-1993 (Percent error of predictions in parentheses)

Year	Actual Day-Use Visits	Predicted Day-Use Visits	Actual Camping Visits	Predicted Camping Visits
a. Black Butte Lake				
1986	284,800	228,200 (-20)	34,800	32,400 (-7)
1987	185,900	277,100 (+49)	22,700	32,300 (+42)
1988	221,800	231,700 (+4)	27,100	22,900 (-15)
1989	248,700	224,500 (-10)	30,400	34,700 (+14)
1990	236,200	225,600 (-4)	28,900	22,800 (-21)
1991	246,200	195,800 (-20)	30,100	32,900 (+9)
1992	291,200	365,300 (+25)	35,600	37,800 (+6)
1993	275,200	292,200 (+6)	33,600	36,800 (+10)
b. Eastman Lake				
1986	94,600	193,700 (+105)	34,900	50,000 (+43)
1987	90,500	81,000 (-10)	33,400	33,300 (0)
1988	74,400	61,800 (-17)	27,500	24,400 (-11)
1989	44,300	70,300 (+59)	16,300	21,500 (+32)
1990	31,400	49,700 (+58)	11,600	15,700 (+35)
1991	31,300	22,000 (-30)	11,600	12,400 (+7)
1992	48,700	42,300 (-13)	18,000	14,100 (-22)
1993	60,300	143,300 (+138)	22,300	33,300 (+49)
c. Hensley Lake				
1986	35,700	88,300 (+147)	58,600	114,600 (+96)
1987	36,000	18,700 (-48)	59,100	34,100 (-42)
1988	32,300	35,500 (+10)	52,900	52,900 (0)
1989	33,100	26,800 (-19)	54,300	50,700 (-7)
1990	39,400	29,700 (-25)	64,700	44,100 (-32)
1991	44,100	41,300 (-6)	72,300	86,100 (+19)
1992	47,100	51,500 (+9)	77,400	76,300 (-1)
1993	43,200	145,900 (+238)	70,900	107,900 (+52)
d. Lake Kaweah				
1986	596,400	961,100 (+61)	31,800	38,000 (+19)
1987	599,100	462,700 (-23)	32,000	28,200 (-12)
1988	657,600	553,800 (-16)	35,100	31,500 (-10)
1989	517,600	669,700 (+29)	27,700	36,300 (+31)
1990	671,400	499,400 (-26)	35,800	25,100 (-30)
1991	654,200	722,800 (+10)	34,900	42,000 (+20)
1992	695,800	499,700 (-28)	37,100	26,300 (-29)
1993	603,500	1,001,100 (+66)	32,200	54,100 (+68)

(Continued)

Table 18 (Concluded)				
Year	Actual Day-Use Visits	Predicted Day-Use Visits	Actual Camping Visits	Predicted Camping Visits
e. Lake Mendocino				
1986	1,148,200	1,019,900 (-11)	219,900	243,800 (+11)
1987	1,150,300	1,022,900 (-11)	220,300	197,900 (-10)
1988	1,032,800	1,524,000 (+48)	197,800	236,100 (+19)
1989	1,049,900	1,228,300 (+17)	201,000	216,900 (+8)
1990	1,150,100	1,259,100 (+9)	220,200	213,900 (-3)
1991	1,083,000	1,091,700 (+1)	207,400	211,300 (+2)
1992	1,084,900	895,400 (-17)	207,700	207,000 (0)
1993	1,087,300	1,629,400 (+50)	208,200	236,200 (+13)
f. New Hogan Lake				
1986	367,000	554,200 (+51)	114,900	139,700 (+22)
1987	325,600	176,900 (-46)	101,900	75,600 (-26)
1988	235,000	138,300 (-41)	73,600	51,400 (-30)
1989	190,400	277,200 (+46)	59,600	70,000 (+17)
1990	215,200	211,400 (-2)	67,400	66,200 (-2)
1991	225,300	189,200 (-16)	70,500	71,200 (+1)
1992	206,100	305,500 (+48)	64,500	86,900 (+35)
1993	362,200	703,100 (+94)	113,400	160,700 (+42)
g. Pine Flat Lake				
1986	656,900	1,523,900 (+132)	100,000	148,500 (+49)
1987	546,500	255,700 (-53)	83,200	62,900 (-24)
1988	435,900	366,600 (-16)	66,300	55,700 (-16)
1989	357,200	354,400 (-1)	54,400	57,600 (+6)
1990	364,900	340,000 (-7)	55,500	52,500 (-5)
1991	399,200	387,000 (-3)	60,700	60,700 (0)
1992	366,900	426,900 (+16)	55,800	60,900 (+9)
1993	540,300	1,277,900 (+137)	82,200	138,700 (+69)
h. Success Lake				
1986	661,200	1,316,800 (+99)	68,500	113,300 (+65)
1987	583,600	262,300 (-55)	60,500	29,400 (-51)
1988	550,400	617,300 (+12)	57,000	53,300 (-6)
1989	543,700	690,200 (+27)	56,400	81,600 (+45)
1990	550,000	420,900 (-23)	57,000	39,400 (-31)
1991	607,500	669,000 (+10)	63,000	83,300 (+32)
1992	567,800	506,000 (-11)	58,800	48,600 (-17)
1993	542,700	1,270,600 (+134)	56,200	111,700 (+99)

Table 19
Site and District Constant Term Adjustment Factors Using Individual District Models

Site	Day-Use Prediction	Camping Prediction
Little Rock District	**0.647**	**1.167**
Beaver Lake	-1.334	1.209
Blue Mountain Lake	1.631	1.671
Bull Shoals Lake	-0.494	0.043
Lake Dardanelle	1.064	0.549
Millwood Lake	0.336	0.802
Nimrod Lake	1.118	0.680
Norfork Lake	0.214	1.945
Table Rock Lake	-0.365	1.116
Nashville District	**1.618**	**0.636**
Center Hill Lake	2.199	1.527
Cheatham Lake	0.747	-0.115
Cordell Hull Lake	1.817	0.916
Dale Hollow Lake	1.481	0.191
J. Percy Priest Lake	1.893	0.168
Lake Barkley	1.239	0.014
Lake Cumberland	1.552	0.603
Laurel River Lake	1.353	---
Sacramento District	**1.267**	**1.133**
Black Butte Lake	0.809	0.383
Eastman Lake	0.642	0.817
Englebright Lake	0.142	0.932
Hensley Lake	-1.108	0.873
Lake Isabella	2.496	2.042
Lake Kaweah	1.472	0.551
Lake Mendocino	0.055	0.912
New Hogan Lake	0.135	0.945
Pine Flat Lake	-0.970	0.057
Success Lake	2.379	1.919

Table 20
Unadjusted Site Visitation Predictions Using Pooled Models

Site	Day-Use Prediction	Camping Prediction
Little Rock District		
Beaver Lake	4,616,200	71,100
Blue Mountain Lake	21,300	9,100
Bull Shoals Lake	2,631,600	123,000
Lake Dardanelle	770,300	112,100
Millwood Lake	457,700	206,500
Nimrod Lake	64,100	18,200
Norfork Lake	1,304,600	48,500
Table Rock Lake	3,100,500	113,900
Nashville District		
Center Hill Lake	4,073,000	285,500
Cheatham Lake	9,660,700	164,400
Cordell Hull Lake	2,668,200	235,200
Dale Hollow Lake	2,885,200	596,200
J. Percy Priest Lake	13,938,400	615,900
Lake Barkley	1,895,200	253,400
Lake Cumberland	3,116,900	173,900
Laurel River Lake	152,300	---
Sacramento District		
Black Butte Lake	297,900	32,100
Eastman Lake	111,100	29,600
Englebright Lake	45,300	12,400
Hensley Lake	264,900	28,000
Lake Isabella	68,300	77,000
Lake Kaweah	246,000	13,100
Lake Mendocino	866,800	322,800
New Hogan Lake	368,400	73,700
Pine Flat Lake	541,100	35,600
Success Lake	219,400	29,600

Table 21
Site and District Constant Term Adjustment Factors Using Pooled Models

Site	Day-Use Prediction	Camping Prediction
Little Rock District		
Beaver Lake	-0.529	1.439
Blue Mountain Lake	2.322	1.052
Bull Shoals Lake	-0.304	-0.507
Lake Dardanelle	1.259	0.853
Millwood Lake	0.551	1.131
Nimrod Lake	1.781	0.799
Norfork Lake	0.485	1.510
Table Rock Lake	-0.266	1.346
Nashville District		
Center Hill Lake	0.490	1.181
Cheatham Lake	-1.080	-0.482
Cordell Hull Lake	0.372	0.278
Dale Hollow Lake	-0.038	-0.299
J. Percy Priest Lake	-0.145	-0.569
Lake Barkley	0.798	0.021
Lake Cumberland	0.108	0.728
Laurel River Lake	-0.296	---
Sacramento District		
Black Butte Lake	0.812	0.860
Eastman Lake	0.550	0.970
Englebright Lake	0.732	0.979
Hensley Lake	-0.942	1.650
Lake Isabella	3.657	2.334
Lake Kaweah	1.513	1.362
Lake Mendocino	1.253	0.623
New Hogan Lake	0.860	1.284
Pine Flat Lake	1.077	1.607
Success Lake	2.007	1.604

Table 22
Average Per-User Consumer Surplus Per Site Using Individual District Models (1994 dollars)

Site	Average Day-Use Benefit ($)	Average Camper Benefit ($)
Little Rock District	**2.23**	**10.22**
Beaver Lake	1.87	9.00
Blue Mountain Lake	5.49	13.25
Bull Shoals Lake	2.16	10.10
Lake Dardanelle	2.97	10.37
Millwood Lake	2.95	10.40
Nimrod Lake	4.46	12.44
Norfork Lake	1.96	9.54
Table Rock Lake	2.36	10.35
Nashville District	**4.82**	**29.77**
Center Hill Lake	6.03	30.28
Cheatham Lake	2.63	29.30
Cordell Hull Lake	4.91	29.56
Dale Hollow Lake	6.43	29.92
J. Percy Priest Lake	5.40	29.45
Lake Barkley	6.23	30.35
Lake Cumberland	5.15	29.61
Laurel River Lake	5.02	0.00
Sacramento District	**2.93**	**10.48**
Black Butte Lake	3.02	10.03
Eastman Lake	4.68	11.41
Englebright Lake	3.08	9.95
Hensley Lake	3.02	9.18
Lake Isabella	6.68	9.94
Lake Kaweah	2.48	7.38
Lake Mendocino	1.87	10.84
New Hogan Lake	4.25	12.10
Pine Flat Lake	3.01	7.94
Success Lake	3.98	9.90

Table 23
Average Annual Total Consumer Surplus Per Site Using Individual District Models (1994 dollars)

Site	Total Day-Use Consumer Surplus ($)	Total Camping Consumer Surplus ($)	Total Consumer Surplus ($)
Little Rock District	**44,566,560**	**29,070,720**	**73,637,280**
Beaver Lake	6,592,860	3,917,520	10,510,380
Blue Mountain Lake	1,589,400	426,240	2,015,640
Bull Shoals Lake	7,452,540	1,833,660	9,286,200
Lake Dardanelle	8,953,560	3,472,920	12,426,480
Millwood Lake	2,672,640	7,106,040	9,778,680
Nimrod Lake	1,938,060	599,940	2,538,000
Norfork Lake	5,857,200	3,164,400	9,021,600
Table Rock Lake	9,510,300	8,550,000	18,060,300
Nashville District	**128,573,820**	**75,562,020**	**204,135,840**
Center Hill Lake	20,964,420	15,786,540	36,750,960
Cheatham Lake	4,388,580	1,513,440	5,902,020
Cordell Hull Lake	9,751,680	5,100,300	14,851,980
Dale Hollow Lake	9,954,180	19,860,480	29,814,660
J. Percy Priest Lake	33,333,480	6,415,380	39,748,860
Lake Barkley	29,527,560	12,511,440	42,039,000
Lake Cumberland	20,220,480	14,374,440	34,594,920
Laurel River Lake	604,080	0	604,080
Sacramento District	**19,979,28**	**10,104,300**	**30,083,580**
Black Butte Lake	771,300	316,080	1,087,380
Eastman Lake	412,200	371,700	783,900
Englebright Lake	319,140	344,160	663,300
Hensley Lake	117,540	582,120	699,660
Lake Isabella	8,964,720	3,334,500	12,299,220
Lake Kaweah	1,647,000	257,580	1,904,580
Lake Mendocino	2,174,580	2,397,600	4,572,180
New Hogan Lake	1,294,380	1,163,880	2,458,260
Pine Flat Lake	1,910,340	753,840	2,664,180
Success Lake	2,368,080	582,840	2,950,920

Table 24
Average Camping Revenue and Total Economic Benefit Per Site (1994 dollars)

Site	Camping Revenue ($)	Economic Benefit ($)
Little Rock District	**8,052,300**	**81,689,580**
Beaver Lake	1,354,680	11,865,060
Blue Mountain Lake	96,480	2,112,120
Bull Shoals Lake	128,700	9,414,900
Lake Dardanelle	961,740	13,388,220
Millwood Lake	2,254,680	12,033,360
Nimrod Lake	126,540	2,664,540
Norfork Lake	1,005,480	10,027,080
Table Rock Lake	2,124,000	20,184,300
Nashville District	**8,226,900**	**212,533,380**
Center Hill Lake	1,700,640	38,451,600
Cheatham Lake	183,960	6,085,980
Cordell Hull Lake	547,560	15,399,540
Dale Hollow Lake	1,954,260	31,768,920
J. Percy Priest Lake	879,480	40,628,340
Lake Barkley	1,600,740	43,639,740
Lake Cumberland	1,360,260	35,955,180
Laurel River Lake	0	604,080
Sacramento District	**3,189,600**	**33,273,180**
Black Butte Lake	95,940	1,183,320
Eastman Lake	90,720	874,620
Englebright Lake	112,320	775,620
Hensley Lake	180,720	880,380
Lake Isabella	1,126,080	13,425,300
Lake Kaweah	105,840	2,010,420
Lake Mendocino	736,380	5,308,560
New Hogan Lake	284,220	2,742,480
Pine Flat Lake	277,560	2,941,740
Success Lake	179,820	3,130,740

Table 25
Visitation Increase and Marginal Benefits for Marginal Increase in Facility Variables

Site	Facility Level	Day-Use Visit Increase	Camping Visit Increase	Marginal Benefit ($)
a. Full-Service Marinas				
Beaver	7	59,840	6,770	172,980
Blue Mountain	0	30,170	3,060	206,100
Bull Shoals	13	34,190	1,650	90,540
Dardanelle	4	79,620	8,090	320,400
Millwood	3	29,350	20,260	297,360
Nimrod	1	25,920	2,630	148,500
Norfork	7	50,720	5,160	148,680
Table Rock	13	39,970	7,500	171,900
Barkley	7	161,860	13,070	1,404,720
Center Hill	7	118,690	16,530	1,216,080
Cheatham	2	142,680	4,090	494,820
Cordell Hull	2	169,550	13,670	1,237,140
Cumberland	10	98,630	11,330	843,300
Dale Hollow	14	28,750	11,450	527,220
J. Percy Priest	4	329,260	10,780	2,095,380
Laurel River	2	10,280	---	51,660
Black Butte	1	30,900	13,540	229,140
Eastman	1	10,670	13,990	209,520
Englebright	1	12,560	14,840	186,300
Hensley	1	4,710	27,230	264,240
Isabella	1	162,610	144,090	2,517,660
Kaweah	0	143,140	29,370	572,400
Mendocino	3	75,450	48,070	662,040
New Hogan	1	36,910	41,310	656,460
Pine Flat	1	76,980	40,770	555,120
Success	0	128,510	49,550	1,001,700
b. Swimming Beaches				
Beaver	11	20,070	2,160	60,660
Blue Mountain	1	8,460	820	57,240
Bull Shoals	15	14,870	680	39,060
Dardanelle	0	152,060	14,710	604,080
Millwood	2	18,690	12,290	183,060
Nimrod	3	6,930	670	39,240
Norfork	9	20,270	1,970	58,500
Table Rock	26	10,450	1,870	43,920
Barkley	11	57,270	4,210	484,380

(Sheet 1 of 5)

Table 25 (Continued)				
Site	Facility Level	Day-Use Visit Increase	Camping Visit Increase	Marginal Benefit ($)
b. Swimming Beaches (Continued)				
Center Hill	9	50,060	6,350	494,100
Cheatham	0	182,980	4,750	620,100
Cordell Hull	9	28,580	2,100	202,500
Cumberland	5	91,870	9,600	757,260
Dale Hollow	12	17,320	6,280	299,160
J. Percy Priest	12	69,010	2,060	433,260
Laurel River	1	7,450	---	37,440
Black Butte	1	930	4,670	49,680
Eastman	1	320	4,830	56,700
Englebright	0	650	9,220	93,780
Hensley	2	100	6,540	60,300
Isabella	0	8,400	89,480	945,180
Kaweah	1	2,430	5,170	44,280
Mendocino	3	2,330	17,490	193,860
New Hogan	1	1,120	14,270	177,300
Pine Flat	1	2,330	14,080	118,800
Success	0	3,730	15,700	170,280
c. Boat Launch Lanes				
Beaver	38	7,500	220	16,020
Blue Mountain	13	1,680	40	9,720
Bull Shoals	88	3,240	40	7,380
Dardanelle	28	8,590	230	27,900
Millwood	31	2,340	420	11,340
Nimrod	20	1,700	40	8,100
Norfork	48	5,070	130	11,160
Table Rock	431	770	40	2,160
Barkley	95	6,680	1,570	89,280
Center Hill	74	6,260	2,540	114,660
Cheatham	21	10,120	850	51,480
Cordell Hull	32	8,080	1,900	95,940
Cumberland	128	4,120	1,380	62,100
Dale Hollow	126	1,660	1,910	67,860
J. Percy Priest	83	9,940	950	81,720
Laurel River	0	11,890	---	59,760
Black Butte	6	33,840	2,740	129,780
Eastman	6	11,690	2,830	86,940
Englebright	4	19,230	4,160	100,620
Hensley	6	5,160	5,500	66,060

(Sheet 2 of 5)

Table 25 (Continued)				
Site	Facility Level	Day-Use Visit Increase	Camping Visit Increase	Marginal Benefit ($)
		c. Boat Launch Lanes (Continued)		
Isabella	27	44,670	7,420	372,060
Kaweah	6	87,970	3,030	240,840
Mendocino	12	83,160	10,450	268,920
New Hogan	6	40,430	8,350	272,700
Pine Flat	12	45,500	4,490	172,440
Success	7	69,150	4,480	319,500
		d. Camping Sites		
Beaver	650	--	150	1,350
Blue Mountain	97	--	70	900
Bull Shoals	985	-	40	360
Dardanelle	425	--	170	1,800
Millwood	330	--	450	4,680
Nimrod	133	--	80	1,080
Norfork	722	--	100	1,260
Table Rock	1,300	--	140	1,260
Barkley	702	--	150	4,500
Center Hill	594	--	230	7,020
Cheatham	58	--	230	6,660
Cordell Hull	492	--	90	2,700
Cumberland	1,104	--	120	3,600
Dale Hollow	1,029	--	170	5,040
J. Percy Priest	671	--	80	2,340
Laurel River	0	--	--	0
Black Butte	120	--	60	540
Eastman	81	--	90	1,080
Englebright	94	--	80	720
Hensley	62	--	230	2,160
Isabella	1,325	--	60	540
Kaweah	95	--	80	540
Mendocino	378	--	130	1,440
New Hogan	220	--	100	1,260
Pine Flat	303	--	70	540
Success	212	--	60	540
		e. Parking Spaces		
Beaver	2,810	210	--	360
Blue Mountain	547	90	--	540
Bull Shoals	2,893	210	--	540
Dardanelle	2,088	240	--	720
				(Sheet 3 of 5)

Table 25 (Continued)				
Site	**Facility Level**	**Day-Use Visit Increase**	**Camping Visit Increase**	**Marginal Benefit ($)**
		e. Parking Spaces (Continued)		
Millwood	1,044	140	--	360
Nimrod	907	80	--	360
Norfork	2,144	240	--	540
Table Rock	7,044	80	--	180
Barkley	4,964	140	--	900
Center Hill	4,819	100	--	540
Cheatham	1,365	200	--	540
Cordell Hull	2,416	140	--	720
Cumberland	7,036	80	--	360
Dale Hollow	5,163	50	--	360
J. Percy Priest	6,770	120	--	720
Laurel River	115	170	--	900
Black Butte	653	90	--	360
Eastman	307	70	--	360
Englebright	240	100	--	360
Hensley	515	20	--	54
Isabella	1,335	240	--	1,620
Kaweah	249	640	--	1,620
Mendocino	620	450	--	900
New Hogan	1,143	60	--	180
Pine Flat	1,361	110	--	360
Success	505	290	--	1,080
		f. Picnic Tables		
Beaver	101	2,280	--	4,320
Blue Mountain	9	880	--	4,860
Bull Shoals	103	2,730	--	5,940
Dardanelle	99	2,470	--	7,380
Millwood	16	4,260	--	12,600
Nimrod	13	2,460	--	10,980
Norfork	14	15,850	--	31,140
Table Rock	85	3,830	--	9,000
Barkley	539	1,710	--	10,620
Center Hill	413	1,600	--	9,720
Cheatham	92	3,440	--	9,000
Cordell Hull	147	2,560	--	12,600
Cumberland	440	1,690	--	8,640
Dale Hollow	164	1,800	--	11,520
J. Percy Priest	531	2,220	--	12,060
				(Sheet 4 of 5)

Table 25 (Concluded)				
Site	Facility Level	Day-Use Visit Increase	Camping Visit Increase	Marginal Benefit ($)
		f. Picnic Tables (Continued)		
Laurel River	20	1,080	--	5,400
Black Butte	45	2,270	--	6,840
Eastman	59	230	--	1,080
Englebright	11	1,340	--	4,140
Hensley	33	180	--	540
Isabella	34	6,070	--	40,500
Kaweah	13	7,360	--	18,180
Mendocino	140	1,310	--	2,520
New Hogan	124	390	--	1,620
Pine Flat	103	970	--	2,880
Success	67	1,390	--	5,580
				(Sheet 5 of 5)

Table 26
Long-Range Visit Forecasts for Nashville District

Site	1990	1995	2000	2005	2010
a. Day-Use Predictions					
Barkley	4,727,300	4,827,100	4,975,300	5,094,000	5,096,900
Center Hill	3,384,600	3,459,900	3,569,200	3,657,900	3,664,900
Cheatham	1,412,600	1,444,400	1,489,800	1,526,800	1,530,500
Cordell Hull	1,879,200	1,920,700	1,981,400	2,030,400	2,033,900
Cumberland	4,489,500	4,591,900	4,739,700	4,860,300	4,872,300
Dale Hollow	1,590,300	1,625,900	1,677,800	1,719,900	1,723,600
J. Percy Priest	7,338,600	7,486,700	7,706,600	7,881,400	7,876,200
Laurel River	120,800	123,500	127,500	130,800	131,100
b. Camping Predictions					
Barkley	415,500	422,600	428,400	433,700	439,000
Center Hill	465,900	473,900	480,500	486,500	492,500
Cheatham	44,100	44,900	45,500	46,100	46,600
Cordell Hull	165,100	167,900	170,200	172,400	174,500
Cumberland	560,300	569,900	577,800	585,100	592,300
Dale Hollow	688,400	700,200	709,900	718,800	727,700
J. Percy Priest	229,600	233,600	236,800	239,700	242,600

Table 27
Proportion of Visitation for Various Per-Person Fee Increases as Compared to Baseline Fees and Average Number of Visitors Per Vehicle[1]

Site	Party Size	$0.25	$0.50	$1.00	$2.00	$3.00
a. Day-Use Fee Increase						
Beaver	2.62	0.707	0.519	0.304	0.133	0.071
Blue Mountain	2.72	0.898	0.811	0.671	0.480	0.360
Bull Shoals	2.54	0.726	0.546	0.335	0.159	0.091
Dardanelle	2.84	0.790	0.637	0.436	0.237	0.148
Millwood	2.47	0.797	0.648	0.448	0.244	0.149
Nimrod	3.11	0.858	0.745	0.577	0.374	0.262
Norfork	2.69	0.709	0.523	0.311	0.141	0.079
Table Rock	3.17	0.709	0.531	0.333	0.172	0.107
Barkley	2.10	0.873	0.774	0.630	0.454	0.349
Center Hill	2.50	0.876	0.777	0.628	0.444	0.335
Cheatham	2.29	0.654	0.476	0.304	0.175	0.121
Cordell Hull	2.57	0.807	0.678	0.517	0.350	0.262
Cumberland	2.91	0.838	0.719	0.556	0.378	0.282
Dale Hollow	2.77	0.880	0.786	0.646	0.474	0.370
J. Percy Priest	2.02	0.873	0.769	0.610	0.413	0.299
Laurel River	2.78	0.838	0.717	0.551	0.369	0.273
Black Butte	2.68	0.821	0.682	0.482	0.273	0.159
Eastman	2.93	0.883	0.784	0.625	0.414	0.287
Englebright	2.51	0.819	0.679	0.481	0.268	0.165
Hensley	2.86	0.814	0.671	0.472	0.260	0.157
Isabella	2.43	0.933	0.871	0.763	0.591	0.466
Kaweah	2.69	0.788	0.630	0.418	0.206	0.114
Mendocino	2.45	0.692	0.503	0.298	0.142	0.086
New Hogan	2.76	0.877	0.774	0.612	0.403	0.281
Pine Flat	2.79	0.824	0.685	0.485	0.263	0.155
Success	2.67	0.862	0.747	0.571	0.352	0.230
b. Camping Fee Increase						
Beaver	2.62	0.894	0.810	0.685	0.528	0.432
Blue Mountain	2.72	0.960	0.923	0.855	0.745	0.658
Bull Shoals	2.54	0.911	0.839	0.730	0.587	0.495
Dardanelle	2.84	0.920	0.853	0.745	0.596	0.498
Millwood	2.47	0.927	0.864	0.763	0.621	0.525
Nimrod	3.11	0.947	0.900	0.819	0.693	0.600
Norfork	2.69	0.905	0.830	0.718	0.575	0.485
Table Rock	3.17	0.913	0.844	0.738	0.599	0.507
Barkley	2.10	0.983	0.967	0.937	0.886	0.842
Center Hill	2.50	0.982	0.965	0.934	0.881	0.836

[1] Fees per vehicle obtained by dividing by average party size.

(Continued)

Table 27 (Concluded)						
Site	Party Size	$0.25	$0.50	$1.00	$2.00	$3.00
b. Camping Fee Increase (Continued)						
Cheatham	2.29	0.978	0.959	0.927	0.874	0.831
Cordell Hull	2.57	0.982	0.965	0.935	0.883	0.840
Cumberland	2.91	0.983	0.967	0.938	0.887	0.844
Dale Hollow	2.77	0.984	0.969	0.942	0.894	0.853
J. Percy Priest	2.02	0.985	0.971	0.944	0.897	0.856
Black Butte	2.68	0.933	0.874	0.775	0.629	0.528
Eastman	2.93	0.950	0.903	0.820	0.687	0.586
Englebright	2.51	0.934	0.877	0.782	0.642	0.544
Hensley	2.86	0.923	0.856	0.744	0.583	0.473
Isabella	2.43	0.973	0.947	0.897	0.811	0.737
Kaweah	2.69	0.895	0.808	0.669	0.485	0.371
Mendocino	2.45	0.921	0.858	0.762	0.635	0.549
New Hogan	2.76	0.948	0.900	0.816	0.684	0.584
Pine Flat	2.79	0.910	0.832	0.704	0.525	0.407
Success	2.67	0.942	0.889	0.797	0.656	0.553

Table 28
Estimated Parameters of Area-Capacity Regressions

Site	β_1 (Linear)	β_2 (Square)	β_3 (cube)	R-Squared
Little Rock District				
Beaver Lake	26.729	0.00141	-9.86*E-9	0.9999
Blue Mountain Lake	2.687	0.00224	-3.48*E-8	0.9999
Bull Shoals Lake	25.770	0.00126	-7.82*E-9	0.9998
Lake Dardanelle	9.931	5.21*E-6	3.53*E-9	0.9998
Millwood Lake	-0.547	0.00028	-5.78*E-10	0.9990
Nimrod Lake	3.715	0.00138	-3.36*E-8	0.9997
Norfork Lake	21.399	0.00210	-2.23*E-8	0.9955
Table Rock Lake	30.699	0.00107	-7.11*E-9	0.9998
Nashville District				
Center Hill Lake	7.496	0.00320	1.87*E-9	0.9999
Cheatham Lake	11.909	0.00016	1.05*E-9	0.9972
Cordell Hull Lake	17.442	0.00043	-4.82*E-9	0.9991
Dale Hollow Lake	14.502	0.00073	-3.84*E-9	0.9993
J. Percy Priest Lake	18.883	0.00063	1.86*E-9	0.9991
Lake Barkley	18.500	-0.00024	3.14*E-9	0.9997
Lake Cumberland	-13.122	0.00200	-3.84*E-9	0.9993
Laurel River Lake	11.384	0.01496	-8.37*E-7	0.9996
Sacramento District				
Black Butte Lake	8.774	0.00490	1.12*E-7	0.9996
Eastman Lake	-9.057	0.05579	-2.02*E-6	0.9994
Englebright Lake	32.409	0.10326	-4.63*E-5	0.9999
Hensley Lake	13.857	0.01285	9.62*E-6	0.9970
Lake Isabella	11.603	0.00242	8.27*E-8	0.9924
Lake Kaweah	20.023	0.01228	8.33*E-6	0.9998
Lake Mendocino				
New Hogan Lake	1.489	0.02398	-1.75*E-6	0.9991
Pine Flat Lake	-5.720	0.03710	-1.31*E-6	0.9999
Success Lake	21.819	0.00536	-9.03*E-8	0.9993

Table 29
Annual Marginal Value per Acre-Foot of Water at Different Surface Acre Levels Based on Tabled Recreation Pool Surface Acres, in 1994 Dollars

Site	Recreation Pool	Percent Full = 90	Percent Full = 80	Percent Full = 70	Percent Full = 60
Little Rock District					
Beaver	28,220	5.89	5.89	6.03	6.21
Blue Mountain	2,910	63.25	65.74	69.89	74.75
Bull Shoals	45,440	2.86	2.81	2.86	2.92
Dardanelle	34,300	22.57	23.99	25.85	27.61
Millwood	29,500	33.35	35.50	38.97	43.58
Nimrod	3,550	77.89	79.29	82.53	86.29
Norfork	22,000	6.55	6.53	6.70	6.93
Table Rock	43,100	6.43	6.30	6.34	6.43
Nashville District					
Center Hill	18,220	21.56	23.20	25.65	28.75
Cheatham	7,450	69.84	67.68	66.55	65.07
Cordell Hull	11,960	62.93	61.49	61.09	60.57
Dale Hollow	27,700	17.60	19.28	21.65	24.46
J. Percy Priest	14,200	118.03	115.51	115.20	114.91
Barkley	57,920	51.48	56.65	61.99	65.48
Cumberland	50,250	6.64	7.06	7.74	8.68
Laurel River	5,660	1.35	1.33	1.35	1.40
Sacramento District					
Black Butte	3,128	10.58	11.52	12.64	13.97
Eastman	1,070	9.47	10.58	12.04	14.02
Englebright	779	8.44	8.50	8.66	8.96
Hensley	1,300	10.35	11.88	13.75	16.09
Isabella	6,520	42.01	46.22	51.17	57.01
Kaweah	1,065	29.39	32.71	36.50	40.86
Mendocino	1,785	31.52	46.48	0.00	0.00
New Hogan	3,099	9.74	10.31	11.09	12.17
Pine Flat	5,956	2.18	2.32	2.52	2.79
Success	2,450	50.18	52.36	54.81	57.47

(Continued)

Table 29 (Concluded)						
Site	Recreation Pool	Percent Full = 50	Percent Full = 40	Percent Full = 30	Percent Full = 20	Percent Full = 10
Little Rock District						
Beaver	28,220	6.44	6.71	7.04	7.36	7.51
Blue Mountain	2,910	81.02	88.16	97.22	108.68	120.67
Bull Shoals	45,440	3.02	3.17	3.37	3.60	3.87
Dardanelle	34,300	29.11	30.06	30.13	28.82	25.25
Millwood	29,500	49.91	59.27	74.81	106.70	222.05
Nimrod	3,550	90.25	95.02	100.24	104.71	106.18
Norfork	22,000	7.24	7.61	8.14	8.77	9.40
Table Rock	43,100	6.57	6.77	7.00	7.27	7.36
Nashville District						
Center Hill	18,220	32.71	38.00	45.58	57.40	78.88
Cheatham	7,450	63.25	60.77	57.40	52.76	45.29
Cordell Hull	11,960	59.80	58.55	56.65	53.44	47.34
Dale Hollow	27,700	27.79	31.70	36.16	40.86	44.06
J. Percy Priest	14,200	114.41	113.38	111.37	107.12	97.29
Barkley	57,920	65.84	62.37	55.30	45.58	33.98
Cumberland	50,250	10.01	12.08	15.73	24.35	79.43
Laurel River	5,660	1.48	1.58	1.78	2.09	2.70
Sacramento District						
Black Butte	3,128	15.61	17.66	20.25	23.65	28.10
Eastman	1,070	16.94	21.55	30.06	51.88	252.92
Englebright	779	9.45	10.19	11.29	12.94	15.61
Hensley	1,300	19.01	22.72	27.38	33.07	39.37
Isabella	6,520	64.04	72.52	82.96	95.76	110.81
Kaweah	1,065	45.83	51.44	57.55	63.79	68.89
Mendocino	1,785	0.00	0.00	0.00	0.00	0.00
New Hogan	3,099	13.70	16.02	19.82	27.09	46.80
Pine Flat	5,956	3.17	3.76	4.77	6.79	13.23
Success	2,450	60.43	63.61	67.12	70.58	73.13

Table 30
Monthly Visitation Proportions (from 1991 NRMS data)

Site	January	February	March	April	May	June	July	August	September	October	November	December
Little Rock District												
Beaver Lake	0.03	0.04	0.03	0.06	0.09	0.14	0.15	0.12	0.14	0.09	0.07	0.05
Blue Mountain Lake	0.03	0.03	0.07	0.10	0.13	0.19	0.22	0.14	0.04	0.03	0.02	0.01
Bull Shoals Lake	0.04	0.05	0.07	0.08	0.07	0.17	0.15	0.14	0.08	0.07	0.05	0.04
Lake Dardanelle	0.05	0.05	0.05	0.09	0.13	0.13	0.14	0.11	0.09	0.08	0.05	0.04
Millwood Lake	0.03	0.03	0.05	0.08	0.03	0.22	0.22	0.13	0.04	0.03	0.02	0.01
Nimrod Lake	0.03	0.04	0.05	0.09	0.09	0.15	0.15	0.18	0.09	0.07	0.04	0.02
Norfork Lake	0.04	0.03	0.07	0.11	0.09	0.12	0.15	0.15	0.08	0.08	0.05	0.03
Table Rock Lake	0.02	0.02	0.03	0.04	0.07	0.18	0.23	0.17	0.12	0.09	0.03	0.02
Nashville District												
Center Hill Lake	0.03	0.03	0.06	0.08	0.11	0.17	0.20	0.16	0.07	0.04	0.04	0.03
Cheatham Lake	0.04	0.03	0.05	0.07	0.09	0.11	0.19	0.13	0.13	0.08	0.05	0.03
Cordell Hull Lake	0.04	0.04	0.05	0.07	0.10	0.14	0.15	0.13	0.10	0.06	0.06	0.06
Dale Hollow Lake	0.01	0.01	0.02	0.02	0.06	0.25	0.28	0.22	0.07	0.03	0.03	0.01
J. Percy Priest Lake	0.02	0.02	0.10	0.10	0.11	0.17	0.19	0.12	0.07	0.06	0.04	0.01
Lake Barkley	0.02	0.03	0.06	0.06	0.10	0.18	0.18	0.13	0.09	0.08	0.05	0.02
Lake Cumberland	0.01	0.02	0.03	0.05	0.08	0.20	0.24	0.19	0.08	0.05	0.03	0.02
Laurel River Lake	0.01	0.01	0.02	0.03	0.06	0.20	0.28	0.24	0.05	0.07	0.03	0.01
Sacramento District												
Black Butte Lake	0.02	0.04	0.12	0.18	0.06	0.15	0.16	0.11	0.08	0.04	0.03	0.01
Eastman Lake	0.06	0.07	0.07	0.14	0.12	0.10	0.11	0.08	0.08	0.07	0.06	0.06
Englebright Lake	0.01	0.02	0.03	0.04	0.14	0.19	0.22	0.19	0.12	0.02	0.02	0.01
Hensley Lake	0.04	0.06	0.12	0.13	0.10	0.12	0.12	0.08	0.08	0.06	0.05	0.04
Lake Isabella	0.03	0.05	0.06	0.08	0.16	0.12	0.13	0.13	0.11	0.07	0.05	0.02
Lake Kaweah	0.04	0.06	0.07	0.13	0.13	0.14	0.14	0.10	0.08	0.04	0.04	0.04
Lake Mendocino	0.02	0.03	0.03	0.11	0.11	0.22	0.17	0.12	0.12	0.03	0.03	0.02
New Hogan Lake	0.04	0.04	0.08	0.11	0.12	0.13	0.13	0.12	0.09	0.06	0.06	0.03
Pine Flat Lake	0.04	0.05	0.07	0.14	0.15	0.17	0.13	0.06	0.09	0.04	0.04	0.03
Success Lake	0.04	0.04	0.10	0.13	0.17	0.15	0.13	0.09	0.07	0.04	0.05	0.01

Table 31
Predicted Visits for Lake Sonoma Using Sacramento District Models

Year	Predicted Day-Use Visits	Predicted Camping Visits	Predicted Total Visits	Actual Total Visits
1988	2,609,300	140,100	2,749,400	501,300
1989	2,765,800	145,900	2,911,700	494,600
1990	3,473,800	149,100	3,622,900	322,100
1991	2,433,700	145,800	2,579,500	367,100
1992	4,089,400	192,900	4,282,300	459,000

Table 32
Model Results for Several Combinations of Estimated Regional Recreation Demand Models. Results Can be Used to Perform Chow Tests of Model Transferability

District(s)	R-Square	Observations	ESS	TOT_COST
a. Day Use				
Little Rock	0.664	307	661.2	-3.442
Nashville	0.559	993	1,718.1	-2.535
Sacramento	0.549	264	980.9	-4.259
Little Rock and Nashville	0.599	1,300	4,178.7	-3.008
Little Rock and Sacramento	0.578	571	1,899.0	-3.792
Nashville and Sacramento	0.537	1,257	5,698.9	-3.378
Pooled, Little Rock, Nashville, Sacramento	0.563	1,564	7,879.6	-3.394
b. Camping				
Little Rock	0.469	616	1,244.4	-1.860
Nashville	0.261	1,755	1,758.4	-0.705
Sacramento	0.446	462	1,334.2	-2.314
Little Rock and Nashville	0.379	2,371	5,782.1	-1.265
Little Rock and Sacramento	0.428	1,078	3,187.7	-2.084
Nashville and Sacramento	0.352	2,217	7,537.9	-1.536
Pooled, Little Rock, Nashville, Sacramento	0.378	2,833	12,000.1	-1.638

Table 33
Chow Tests of Model Coefficient Equality Required for Valid Model Transferability

Base District Model	Transferred To	Day-Use Test Statistic	Camping Test Statistic
Little Rock and Nashville	Sacramento	116.7	276.9
Little Rock and Sacramento	Nashville	261.3	575.8
Nashville and Sacramento	Little Rock	53.0	148.3
Little Rock	Nashville	240.3	135.4

Table 34
Average Per-User Consumer Surplus Using Pooled Models from Other Two Districts, Percent Difference from Individual District Models (in 1994 dollars)

Site	Average Day-Use Benefit	Percent Difference	Average Camper Benefit	Percent Difference
Little Rock District				
Beaver Lake	2.09	+12	12.47	+38
Blue Mountain Lake	5.69	+4	15.55	+17
Bull Shoals Lake	2.20	+2	13.23	+31
Lake Dardanelle	3.10	+4	13.39	+29
Millwood Lake	3.15	+7	13.27	+28
Nimrod Lake	4.57	+2	15.12	+22
Norfork Lake	2.00	+2	12.74	+34
Table Rock Lake	2.20	-7	13.39	+29
Nashville District				
Center Hill Lake	2.63	-56	11.09	-63
Cheatham Lake	0.85	-68	7.04	-76
Cordell Hull Lake	1.49	-70	10.39	-65
Dale Hollow Lake	2.47	-62	12.06	-60
J. Percy Priest Lake	2.52	-53	8.73	-70
Lake Barkley	2.43	-61	10.98	-64
Lake Cumberland	1.76	-66	10.12	-66
Laurel River Lake	1.85	-63		
Sacramento District				
Black Butte Lake	5.35	+77	17.69	+76
Eastman Lake	7.27	+55	18.14	+59
Englebright Lake	5.54	+80	16.92	+70
Hensley Lake	5.51	+82	17.30	+88
Lake Isabella	8.57	+28	15.71	+58
Lake Kaweah	4.39	+77	17.23	+133
Lake Mendocino	4.32	+131	17.48	+61
New Hogan Lake	6.32	+49	20.16	+67
Pine Flat Lake	4.91	+63	17.75	+124
Success Lake	6.53	+64	17.96	+81

Appendix A
Summary of Visitation Patterns for Omaha District Exit Surveys

As part of a recreation economic benefits analysis of the Missouri River System (U.S. Army Engineer Division, Missouri River, 1994), respondents in an exit survey in the Omaha District were asked whether they were on a multidestination trip. While surveys were conducted at many sites, the results from two sites are presented here because the sample sizes are large enough to split into different categories. These sites are General Sibley Park located on Lake Oahe near Bismarck, North Dakota, and Lake Sakakawea State Park on Lake Sakakawea near Garrison, North Dakota.

All sampled visitors were classified as day users or campers and as single- or multiple-destination visitors. Market areas were defined as 125 miles for day users and 175 miles for campers, similar to the three district models. The results are presented in Table A1. A total of 1,874 visitors were surveyed at General Sibley Park, and 1,241 visitors were surveyed at Lake Sakakawea State Park. Overall, the majority of all visitors were on single-destination trips (87.9 percent).

The two potential sources of error with the market area specification presented in the three district models are that many multiple-destination travelers would be included in the market area, and single-destination visitors would be excluded; Table A1 shows that these errors may be small.

For General Sibley Park, the market areas include 96.6 percent of single-destination day users and 90.9 percent of single-destination campers. For Lake Sakakawea State Park, the market areas include 80.4 percent of all single-destination day users and 84.6 percent of single-destination campers. The concern that the market areas exclude many single-destination travelers does not seem to be too important for these sites. Considering all visitors at both sites, over 90 percent of all single-destination visitors are included in the defined market areas.

Table A1
Classification of Omaha District Visitors

General Sibley Park Day Users			
	Within 125-Mile Market Area	Outside 125-Mile Market Area	Total
Primary-Destination Visitors	1,410	49	1,459
Multiple-Destination Visitors	92	23	115
Total Visitors	1,502	72	1,574
General Sibley Park Campers			
	Within 175-Mile Market Area	Outside 175-Mile Market Area	Total
Primary-Destination Visitors	189	19	208
Multiple-Destination Visitors	41	51	92
Total Visitors	230	70	300
Lake Sakakawea State Park Day Users			
	Within 125-Mile Market Area	Outside 125-Mile Market Area	Total
Primary-Destination Visitors	469	114	583
Multiple-Destination Visitors	34	52	86
Total Visitors	503	166	669
Lake Sakakawea State Park Campers			
	Within 175-Mile Market Area	Outside 175-Mile Market Area	Total
Primary-Destination Visitors	413	75	488
Multiple-Destination Visitors	40	44	84
Total Visitors	453	119	572

The other concern is that many multiple-destination visitors could be included in the market areas. Again, this concern does not seem to be significant. For General Sibley Park, the market areas include 6.1 percent multiple-destination day users and 17.8 percent multiple-destination campers; for Lake Sakakawea State Park, the market areas include 6.8 percent multiple-destination day users and 8.8 percent multiple-destination campers. The overall market areas include only about 8 percent multidestination visitors.

Assuming similar visitation patterns in the Little Rock, Nashville, and Sacramento Districts, the market area definitions should not bias this study's benefit estimates significantly. The results from the Omaha District show that the defined market areas include the majority of all single-destination visitors and include few multiple-destination travelers.

Appendix B
Valuing Individual Facilities Using the Facility Index

Simulation experiments were used to explore the performance of the facility index approach described in Chapter 4 of this report relative to other methods for dealing with multicollinearity. Along with the index, the experiments will consider using ordinary least squares (OLS) with all facility variables, dropping all but one facility variable, and principal components. Wetzstein and Green (1978)[1] applied principal components to a recreation demand situation. Ridge regression was not included in the experiments, because it has received little use in economic research, involves the choice of an arbitrary constant, and was more difficult to operationalize.

The same dataset is used for all simulation experiments. The data on the independent variables are taken from the Sacramento District data included in the main text of this report. A 150-mile market area was chosen as a midpoint between the day-use and camping market areas. This produced 348 observations. The following independent variables were included in the experiments:

- POPULATION
- TOT_COST
- SUB_INDEX
- CV
- SUR_ACRES
- PICNIC
- LANES
- PARKING

Note that the last four variables in this list are the facility variables used to construct the facility index. The first four variables are the "nonfacility" variables, which are assumed to be relatively uncorrelated among each other and with the facility variables.

---

[1] References are listed with complete information following main text.

To illustrate the degree and impact of multicollinearity, a regression model is estimated using the independent variables above and the dependent variable on estimated Sacramento annual day-use visitation. The results are given in Table B1. The auxiliary R^2 values for each independent variable result from regressing that variable against all remaining independent variables. Greene (1993) presents a rule of thumb stating that if any of the auxiliary R^2's are higher than the R^2 of the full regression, then multicollinearity is a concern. Noting the high auxiliary R^2's in Table B1, especially for PARKING and SUR_ACRES, multicollinearity seems to be problematic. While the parameter estimates for the nonfacility variables correspond to expectations, those for the facility variables do not. Parameter estimates for the facility variables are expected to range between 0 and 1 (decreasing marginal impact on visitation). The estimate on PARKING, which has the highest auxiliary R^2, is especially difficult to accept. Using the parameter estimates in Table B1 would produce some management actions that may not be supported reliably.

Different methods for dealing with multicollinearity are tested using simulations. Each simulation involves running regressions with the actual independent variable, but a generated dependent variable. The values for the dependent variables are generated using known coefficients and error variances. For all simulations, the values of the nonfacility coefficients are defined as:

$$
\begin{aligned}
\beta_0 &= 4.28 \\
\beta_{\text{POPULATION}} &= 1.03 \\
\beta_{\text{TOT\_COST}} &= -3.27 \\
\beta_{\text{SUB\_INDEX}} &= -14.30 \\
\beta_{\text{CV}} &= -0.94
\end{aligned}
$$

where

β_0 = intercept term in the double-log models

These values were chosen because they approximate the estimates obtained using the actual data and generate a mean of the dependent variable similar to the actual mean.

For the known coefficients on the facility variables, two possibilities are explored. First, all four facility coefficients are set equal at 0.50. In the other case, the coefficients are set differently as:

$$
\begin{aligned}
\beta_{\text{SUR\_ACRES}} &= 0.79 \\
\beta_{\text{PICNIC}} &= 0.44 \\
\beta_{\text{PARKING}} &= 0.66 \\
\beta_{\text{LANES}} &= 0.32
\end{aligned}
$$

Each simulation run generates 100 random values of an error term with a known variance (σ^2). The values of σ^2 defined in this experiment are 1.6, 2.8, and 4.7. Setting σ^2 at 1.6 approximates the R^2 obtained with the actual data,

around 0.65. The other values of σ^2 produce R^2's that represent reasonable values obtained in travel cost models. Setting σ^2 at 2.8 gives an average R^2 of about 0.40, and R^2 is about 0.20 when σ^2 is 4.7. Note that the R^2's of the models in the text of this report range from 0.35 to 0.67. Different error variances will indicate if the methods compare differently as the explanatory power of the model changes. Thus, with three error variances and two sets of coefficients, six total simulation runs are presented.

The first approach for dealing with multicollinearity is to include all four facility variables, along with the nonfacility variables, in an OLS regression. This technique should give unbiased but unstable estimates. The next approach is to include only one of the facility variables, SUR_ACRES, as a proxy for facility levels at a reservoir. Thus, the other three facility variables are dropped from the model to reduce multicollinearity. This method does not allow for management analysis of other facility variables.

The third method is principal components analysis (PCA), which should produce biased coefficients with lower variances than the full OLS model. With PCA, one must choose how many characteristic vectors to include in calculating the estimates. For this experiment, the use of one, two, and three characteristic vectors will be explored. If all characteristic vectors are included, PCA will produce the same results as OLS with the full set of regressors.

The final approach is the facility index described in Chapter 4 of this report. The index is constructed by running four first-stage double-log regressions with the simulated dependent variable. In each of these regressions, all four nonfacility variables are included along with one facility variable. Define each upward biased first-stage coefficient on a facility variable as T_i. The facility index is then calculated as

$$I_i = \left(\mathrm{SUR\_ACRES}_i^{\ \beta\mathrm{SUR\_ACRES}}\right) * \left(\mathrm{PICNIC}_i^{\ \beta\mathrm{PICNIC}}\right)$$

$$* \left(\mathrm{PARKING}_i^{\ \beta\mathrm{PARKING}}\right) * \left(\mathrm{LANES}_i^{\ \beta\mathrm{LANES}}\right)$$

The variable I_i is then included in a second-stage double-log OLS model with the four nonfacility variables. Because the model is Cobb-Douglas in structure, the estimated coefficient on INDEX can then be multiplied by each T_i to obtain the final coefficient estimates for the facility variables.

The four methods will be compared using the mean squared error criterion, defined as the bias squared plus the variance of the parameter estimate. Desirable point estimators should seek to minimize mean square error (MSE) (Mendenhall, Waherly, and Sheaffer 1990 (p 339)).

All results were obtained using SAS® regression software. The results of the simulations are presented in Tables B2 through B4. Each table reports on

a different value of σ^2. All values of mean square error (MSE) presented in the tables have been standardized by dividing through by the mean of the variable. The total MSE of each simulation is the sum of all four standardized MSE's.

In general, the simulation results show that PCA and the index method produce lower MSE's than OLS with the full set of regressors. While OLS produced unbiased parameter estimates, the variances on the coefficients are large.

Using SUR_ACRES as the only facility variable produced a coefficient that was biased considerably upwards. When the coefficient on SUR_ACRES was set at 0.79, its estimate averaged about 1.6, about twice too high. When the coefficient was set at 0.50, an average estimate of 1.3 was produced, more than twice too high. These findings suggest that management analysis based on these biased coefficients will be in error if based on regression models estimated by dropping variables to reduce multicollinearity.

The index performs better in terms of low MSE's for the case where all facility coefficients are set equal at 0.50. When the coefficients are the same, the index method outperforms PCA in terms of MSE in every case. However, when the facility coefficients are set unequal, using PCA produces lower MSE's than the index when $\sigma^2 = 1.6$. The index method performs better, relative to PCA as the value of σ^2 increases.

As more characteristic vectors are included, PCA produces higher MSE's. More characteristic vectors decrease the bias but increase the variances. These results suggest using only one characteristic vector in PCA.

In all scenarios in this simulation experiment, the use of the facility index produced lower MSE's than OLS with all regressors and dropping variables. In five of the six scenarios, the facility index produced lower MSE's than PCA. The results of this experiment suggest that using the facility index may produce lower MSE's than other methods for dealing with multicollinearity.

Table B1
Regression Results Using Actual Dependent Variable (Sacramento Day Use, 150-Mile Market Area)

Variable	Parameter Estimate	Standard Error	Auxiliary R^2
Intercept	5.062	5.103	---
POPULATION	0.989	0.084	0.20
TOT_COST	-3.938	0.201	0.13
SUB_INDEX	-0.163	0.505	0.37
CV	-0.699	0.130	0.34
SUR_ACRES	1.145	0.353	0.83
PICNIC	1.704	0.312	0.38
LANES	0.432	0.197	0.61
PARKING	-1.516	0.497	0.88

Table B2
MSE Simulation Results, σ^2 = 1.6

Method	SURACRES	PICNIC	PARKING	LANES	Total MSE
Coefficients Different					
OLS (All variables)	0.1205	0.0652	0.2803	0.2044	0.6704
OLS (SURACRES only)	0.9667	--	--	--	--
PCA (1 c.v.)	0.0629	0.0418	0.0265	0.1134	0.2441
PCA (2 c.v.'s)	0.0687	0.0989	0.0308	0.1634	0.3618
PCA (3 c.v.'s)	0.0577	0.0607	0.0574	0.1903	0.3661
Facility Index	0.0457	0.0043	0.0121	0.3509	0.4130
Coefficients Same					
OLS (All variables)	0.1730	0.0578	0.3886	0.1474	0.7668
OLS (SURACRES only)	0.7069	--	--	--	--
PCA (1 c.v.)	0.0262	0.0222	0.0346	0.0278	0.1108
PCA (2 c.v.'s)	0.0280	0.0794	0.0276	0.0884	0.2234
PCA (3 c.v.'s)	0.0788	0.0520	0.0712	0.1462	0.3482
Facility Index	0.0060	0.0322	0.0282	0.0304	0.0968

Table B3
MSE Simulation Results, σ^2 = 2.8

Method	SURACRES	PICNIC	PARKING	LANES	Total MSE
Coefficients Different					
OLS (All variables)	0.3148	0.2425	0.7024	0.5069	1.7666
OLS (SURACRES only)	0.9319	--	--	--	--
PCA (1 c.v.)	0.0981	0.1093	0.0848	0.2006	0.4928
PCA (2 c.v.'s)	0.1028	0.2450	0.1038	0.4109	0.8625
PCA (3 c.v.'s)	0.1697	0.2284	0.1692	0.4834	1.0507
Facility Index	0.0578	0.0139	0.0218	0.3881	0.4816
Coefficients Same					
OLS (All variables)	0.4320	0.1502	0.7962	0.3412	1.7196
OLS (SURACRES only)	1.5680	--	--	--	--
PCA (1 c.v.)	0.0836	0.0626	0.1002	0.0606	0.3070
PCA (2 c.v.'s)	0.0918	0.1552	0.1100	0.2208	0.5778
PCA (3 c.v.'s)	0.2112	0.1410	0.1666	0.3236	0.8424
Facility Index	0.0130	0.0372	0.0498	0.0504	0.1504

Table B4
MSE Simulation Results, σ^2 = 4.7

Method	SURACRES	PICNIC	PARKING	LANES	Total MSE
Coefficients Different					
OLS (All variables)	0.9185	0.4548	1.8568	1.5631	4.7932
OLS (SURACRES only)	1.2203	--	--	--	--
PCA (1 c.v.)	0.2512	0.3011	0.2810	0.4179	1.2512
PCA (2 c.v.'s)	0.2622	0.5876	0.3167	1.1804	2.3469
PCA (3 c.v.'s)	0.5788	0.5022	0.5103	1.5309	3.1222
Facility Index	0.0570	0.0261	0.0600	0.6006	0.7437
Coefficients Same					
OLS (All variables)	1.1690	0.5426	2.3712	1.0478	5.1306
OLS (SURACRES only)	1.7567	--	--	--	--
PCA (1 c.v.)	0.3142	0.2358	0.3580	0.2074	1.1154
PCA (2 c.v.'s)	0.3310	0.5432	0.4140	0.7384	2.0266
PCA (3 c.v.'s)	0.7624	0.5446	0.6158	1.0172	2.9400
Facility Index	0.0532	0.0464	0.0966	0.1260	0.3222

Appendix C
Estimating the Impact of Reduced Water Levels Through Outside Data

As discussed in the text, estimation of a coefficient on the variable PCT_FULL using the survey data proved difficult. The survey's years do not provide enough variability on PCT_FULL to estimate a coefficient reliability. Data that cover a longer period present more variability on PCT_FULL and should increase the reliability of the parameter estimate.

A supplementary dataset that covers the years 1985 through 1991 was constructed. During this period, drought conditions existed at least occasionally in all districts. Information was collected for all sites included in the three district models. The data include the following variables:

- VISITS — Total annual site visitation (day use and camping)
- SUR_ACRES — Surface acres of the site at the recreation pool
- PARKING — Number of parking spaces at the site
- MILES — Number of road miles from the site to the nearest metropolitan statistical area (MSA)
- POPULATION — Population of the nearest MSA from 1980 census
- PCT_FULL — Weighted average of surface acres divided by surface acres at the recreation pool

To calculate PCT_FULL, the average surface acres for each month is multiplied by the proportion of visitation occurring in that month. These are summed to produce a weighted average for surface acres. The weighted average is then divided by the surface acres at the recreation pool. For sites located near several MSA's, the value of MILES reflects a population weighted average.

A double-log regression for each of the three districts was estimated using visits as the dependent variable. A trend variable (the year) was also included to account for shifts during the years of analysis, such as population changes

or changes in recreation behavior. The results are given in Table C1. The coefficient on PCT_FULL varies across the three districts. One may question whether this difference should exist, especially between the Little Rock and Nashville Districts. Similar to the survey data, the most variability in PCT_FULL occurs in the Sacramento District. Even with additional years included in the model, less variability in PCT_FULL in the other districts may make estimation difficult.

To obtain more variability, the Little Rock and Nashville districts were pooled and a regression was estimated. The results are given in Table C2. Note that the estimated parameter on PCT_FULL (1.275) is now similar to that estimated in the Sacramento District (1.103).

The most reliable coefficient on PCT_FULL is 1.275 for the Little Rock and Nashville Districts and 1.103 for the Sacramento District. Without the pooling of the Little Rock and Nashville Districts, the difference in the coefficient on PCT_FULL between the two districts seems unsupported.

A model that pooled all three districts was also estimated. The results are presented in Table C3. The estimated parameter on PCT_FULL is 1.152. Because double-log models were estimated, coefficients are elasticities and are therefore used directly for the pooled model in Table 15 in the main text. The coefficients on PCT_FULL obtained in this appendix were entered as restrictions in Table 15.

Table C1
District Regression Results Using Outside Data

Variable	Coefficient	T-Statistic
Little Rock District (n = 36, R^2 = 0.909)		
Intercept	71.226	
SUR_ACRES	0.593	4.121
PARKING	0.277	1.610
MILES	0.402	2.263
POPULATION	0.266	1.815
Trend	-0.040	-1.952
PCT_FULL	2.176	3.775
Nashville District (n = 56, R^2 = 0.959)		
Intercept	-133.974	
SUR_ACRES	0.228	1.164
PARKING	0.658	5.548
MILES	-0.309	-2.085
POPULATION	0.213	1.564
Trend	0.069	4.149
PCT_FULL	0.541	0.305
Sacramento District (n = 62, R^2 = 0.477)		
Intercept	-53.496	
SUR_ACRES	1.421	3.451
PARKING	-0.828	-1.815
MILES	-0.647	-2.025
POPULATION	0.287	2.432
Trend	0.028	0.528
PCT_FULL	1.103	3.940

Table C2
Pooled Little Rock and Nashville District Regression Results ($n = 92$, $R^2 = 0.917$)

Variable	Coefficient	T-Statistic
Intercept	-54.024	
SUR_ACRES	0.213	2.841
PARKING	0.681	11.830
MILES	-0.293	-5.152
POPULATION	0.065	1.055
Trend	0.028	1.851
PCT_FULL	1.275	2.508

Table C3
Three-District Pooled Regression Results ($n = 154$, $R^2 = 0.856$)

Variable	Coefficient	T-Statistic
Intercept	-56.798	
SUR_ACRES	0.372	5.590
PARKING	0.509	6.591
MILES	-0.356	-3.042
POPULATION	0.232	3.734
Trend	0.029	1.260
PCT_FULL	1.152	6.820

Appendix D
Effect of Climate on Visitation

Application of the three-district pooled models to other districts may produce poor results due to differences in climate. Even if recreation is similar in another district, a shorter or longer recreation season may be expected to produce different visitation totals.

The impact of climate on site visitation totals was tested using climatic data from Conway and Liston (1974) and the USACE's Natural Resources Management System (NRMS) database. A total of 115 USACE sites, representing a sample from all areas of the United States, are included in the data. Some, but not all, sites from the Little Rock, Nashville, and Sacramento Districts are included in this dataset. Regression models are defined with total annual visitation (day-use and camping) to a USACE site as the dependent variable. From the NRMS database, the following site-specific independent variables are included:

a. The recreation pool size of the reservoir, in surface acres.

b. The distance (in miles) from a location at the USACE site to the nearest metropolitan statistical area (MSA).

c. The population of the nearest MSA.

For some sites, more than one nearby MSA is listed in the NRMS database. In such cases, the distance variable is defined as a weighted distance. The population of each MSA is used to assign the relative weights. The population totals for these observations is the sum of the population of each MSA.

Several climate variables were included to account for differences in temperature, length of recreation season, rainfall, and humidity. The potential climate variable includes:

a. Average annual temperature.

b. Average annual maximum temperature.

c. Average maximum July temperature.

d. Average July noon relative humidity.

e. Average July cooling degree days.

f. Average annual cooling degree days.

g. Average July rainfall.

h. Average number of days in July with rain (0.01 in. or more).

The July variables are assumed to represent conditions during the peak visitation period while annual variables represent the length of the recreation season. A cooling-degree day is defined as the positive difference, in degrees Fahrenheit, between the average maximum daily temperature and 65 deg. Thus, if the average maximum temperature is less than 65 deg, then the daily total for cooling degree days is zero. Monthly and yearly totals for cooling degrees are simply the sum of individual days.

Regression models were estimated using the variables from the NRMS data and various combinations of the climate variables. The model with the best performance is presented in Table D1. The two climate variables which perform best are the average annual cooling degree days and the average July humidity. The equation is in double-log format, so all coefficients are elasticities. All estimated coefficients are significant and have the expected signs. Visitation increases as the annual cooling-degree days and humidity increase.

Table D1
Regression Results Using National USACE Dataset

Variable	Parameter Estimate	Standard Error
Intercept	-1.8858	0.868[1]
Miles to MSA	-0.3117	0.071[2]
Pop. of MSA	0.3535	0.083[2]
Surface Acres	0.4737	0.050[2]
Avg. July Humidity	1.0877	0.441[3]
Avg. Annual Cooling Degree Days	0.4668	0.123[2]

[1] Significant at the 0.10 level.
[2] Significant at the 0.01 level.
[3] Significant at the 0.05 level.

The effect of these climate variables can be incorporated into the pooled models by using the estimated coefficients as adjustment factors. To illustrate the effect of climate, a combination of cooling-degree days and July humidity can be used as a baseline. The average of these two variables makes a reasonable choice for a baseline. The average annual cooling-degree days is

1,271, and the average July humidity is 52.8. Set predicted visits equal to 1 for the average values of these variables. Deviation from these averages necessitates an adjustment. Table D2 presents an example of how visitation changes as the climate variables change. The top row has values of average annual cooling-degree days, and the first column has values of average July humidity. The appropriate adjustment factor is given as the intersection of the two based on the above baseline. These adjustment factors can be applied to any situation by using the appropriate baseline visitation prediction. Table D2 shows that this adjustment can be significant. Visitation in an area with a long, hot, and humid recreation season can be 10 times higher than in an area with a shorter, less humid recreation season.

Table D2
Sample Adjustment of Visitation Prediction Based on Climate Variables

COOLING_DD HUMIDITY	400	800	1200	1600	2000	2400	2800
20 percent	0.203	0.280	0.338	0.387	0.423	0.468	0.503
30 percent	0.315	0.435	0.523	0.601	0.668	0.727	0.781
40 percent	0.431	0.596	0.720	0.823	0.914	0.995	1.069
50 percent	0.550	0.759	0.918	1.050	1.165	1.268	1.363
60 percent	0.670	0.925	1.118	1.279	1.419	1.545	1.661
70 percent	0.792	1.095	1.323	1.513	1.679	1.828	1.964
80 percent	0.916	1.266	1.530	1.749	1.941	2.114	2.272

Appendix E Graphical Illustration of Selected Management Applications

Introduction

This section presents results of selected applications graphically. One application is selected for each of the three district specific models. Illustration of changes in demand curves as a result of management actions changes helps visualize the economic benefits or costs of the change. For each application, the baseline site demand curve is presented. Baseline consumer surplus (benefits) is the area under the baseline demand curves. A shift in demand is then illustrated for each proposed management action, for which resulting change in consumer surplus to visitors is shown.

All three applications use a base year of 1991. Thus, the data used to apply the models needed to be updated so variables are at 1991 levels. Data collection for model updating can be time consuming. Some variables, such as water quality or detailed demographic data, may be difficult to obtain for the year of the application. This may be especially true for recent years for which data are not yet published. If data are unavailable for the application year, then data should be used for the nearest year they are available. Some variables are important for updating and easy to obtain. County population is normally available on a yearly basis. Other demographic variables should be updated if possible. Changes in vehicle operations costs should be updated where possible. All dollar values should be deflated to 1980 dollars since the original models were fit with dollars in those units. Data on price inflation rates from 1980 to the year of the application are needed to perform this deflation.

Once all possible variables are updated, the model can be used to obtain visit predictions for the market areas. These can be compared with known visitation totals to obtain the appropriate calibration factors so the model correctly predicts base visitation. This process is further explained.

Addition of Camp Sites at Table Rock Lake

This first application is described in the most detail, because the methods are similar for all three. For all applications, 1991 is the base year. This means that the models compare actual visitation and benefits for 1991 with model-predicted visitation and benefits with the proposed management action for 1991. The first step in applying demand curves is to isolate and update the data for the project under study. Because the addition of camp sites to Table Rock Lake is assumed to affect only camping visitors, day-use visitation and benefits are unchanged.

The 175-mile camping market area for Table Rock Lake includes 85 counties. A dataset including these counties as 85 observations was constructed for the application. Variables were updated where possible. Dollar-denominated variables including vehicle operations costs and county per capita income, were deflated to 1980 constant dollars. Observed water data at the project level for 1991 were used to define the values of PCT_FULL and CV. Because 1991 water quality data were not available, average values for data during the survey years were used.

The Little Rock District camping model presented in Table 12 was then applied to the 1991 data set for each of the 85 counties. Use of the model as described produced an unadjusted camping market area prediction of 134,800 visitors when summed over the 85 counties. Actual Table Rock Lake camping visitation for 1991 is estimated at 906,000. A multiplicative adjustment can be used to adjust the prediction beyond the market area and to correct for any log transformation bias (described in Chapter 5). In this case, the calibration factor is 906,000/134,800 = 6.72. Multiplying model-predicted visits of 124,800 by 6.72 calibrates the model to predict the 906,000 visitors.

The result of this exercise produces one point along the base scenario demand curve. At the existing camping fee, 906,000 campers visited in 1991. Figure E1 shows this point along the X-axis at an added price of zero for the left curve. Additional points along the left demand curve indicate how visitation changes as the price of a camping visit is increased beyond the base price due to entry fees or increases in travel costs. In travel cost analysis, an increase in price is normally represented by an increase in the user fee. Consumer surplus is measured as the area under the demand curve above the existing price or fee level.

To obtain additional points along the left demand curve in Figure E1, the value of TOT_COST is increased. The model is based on 1980 dollars, so increases in price must also be in 1980 dollars. Also, increases in price must be computed on a per-visit basis since all travel costs are defined as a per-user basis (Chapter 3). The results can be placed on a per-vehicle basis by adjusting for the number of visitors in a vehicle (Table 27b, main text).

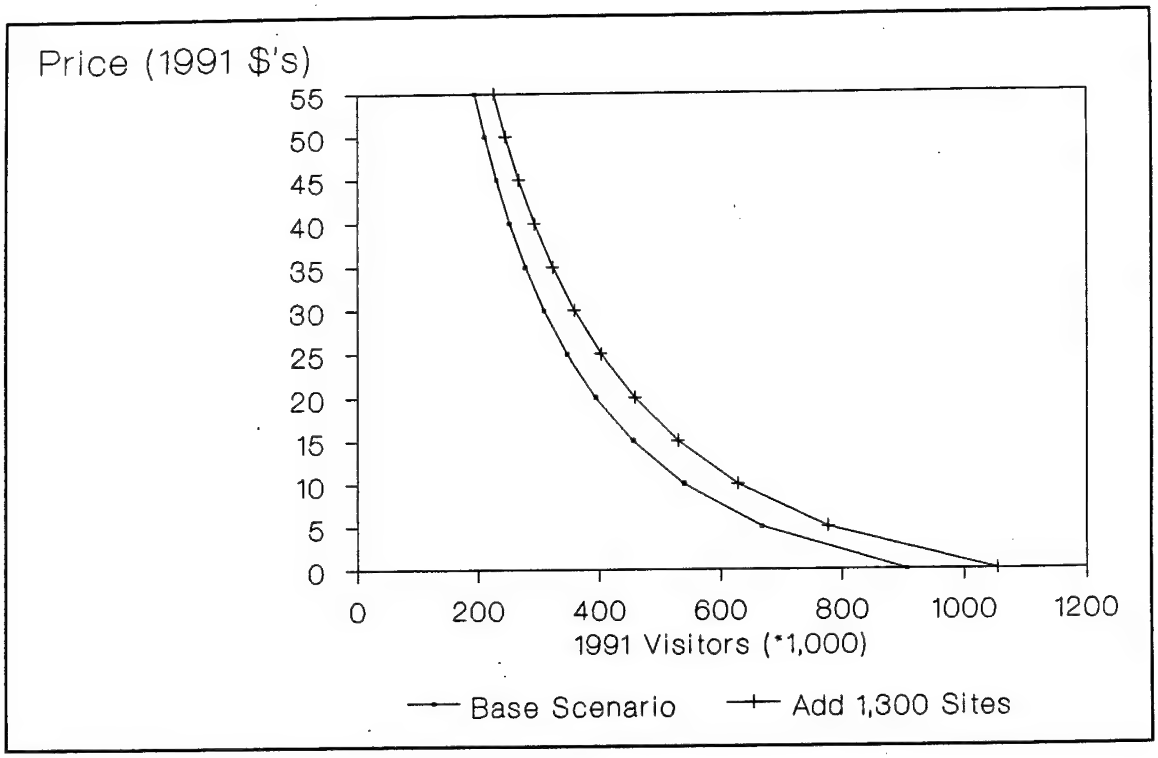

Figure E1. Campsite demand, Table Rock Lake

Consider in detail how to obtain a second point along the base demand curve in Figure E1. Managers may wish to know the impact of a $5.00 addition to the camping fee (in 1991 dollars) on the number of 1991 camping visitors to Table Rock Lake. The calculations need to convert a $5.00 per-vehicle fee in 1991 dollars to an equivalent per-visitor fee in 1980 dollars. First, Table 27b indicates that a vehicle visiting Table Rock Lake contains an average of 3.17 visitors. Thus, a $5.00 fee per vehicle equates to a $1.58 fee per person (assuming that the fee is divided among the members of the vehicle). Next, the $1.58 fee in 1991 dollars needs to be converted to 1980 dollars. Data from the Federal Reserve Bank of St. Louis (1995) show that the consumer price index was 136.3 in 1991 and 82.4 in 1980. The appropriate deflation factor from 1991 dollars to 1980 dollars is 82.4/136.3 = 0.605. Thus, a $1.58 fee increase in 1991 dollars is equivalent to a 1.58 * 0.605 = $0.96 vehicle fee increase in 1980 dollars.

The value of TOT_COST is increased for all 85 county observations by $0.96 to obtain the point on the demand curve in Figure E1 corresponding to a $5.00 increase in the camping price for 1991. The model produces an unadjusted prediction of 99,400 camping visitors for the $5.00 increase. This unadjusted prediction is multiplied by the same calibration factor described above (6.72) to produce an adjusted prediction of 668,000. Note that the left demand curve in Figure E1 passes through the point of a $5.00 increase in price at 668,000 visitors.

The rest of the demand curve is plotted by increasing the price further and continuing to trace out new visit predictions. The two important steps to remember are the conversion to the appropriate per-user fee in 1980 dollars and adjusting the raw visit prediction produced by the model. The full base demand curve is illustrated in Figure E1.

The demand curve is plotted up to about a $55 increase in price. This limit corresponds to the maximum observed travel cost in the Little Rock District (Chapter 5, paragraph entitled "Benefits per visit"). The model can not be used reliably to estimate the demand curve further. Chapter 5 presents the maximum observed travel cost for the Little Rock District as $34.58 in 1980 dollars, which is about $57 in 1991 dollars. Figure E1 reflects this limit.

One can also estimate the total camping benefits of Table Rock Lake using Figure E1. Chapter 5 indicates that total benefits are measured as the area under the demand curve up to the maximum observed travel cost in the visitor market area. In Figure E1, total base benefits are the area under the base demand curve to the right of a vertical line drawn down from the top of the graph and underneath the $55 price horizontal. Table 22 gives the per-user benefit for campers to Table Rock Lake at $10.35 in 1994 dollars. This is $9.51 in 1991 dollars. Because there were 906,000 camping visitors to Table Rock Lake in 1991, total camping benefits are estimated to be $8.6 million in 1991 dollars. The area under the base demand curve in Figure E1 can be approximately measured as about $8.6 million. Thus, the numerical calculation is consistent with the graphical presentation.

The right-hand demand curve presented in Figure E1 corresponds results of an increase in the number of camp sites from 1,300 to 2,600. Such a large change in camp sites was considered for the difference between the demand curves to be visible on the graph. The new demand curve was obtained in the same way as the first except the value of CAMPS was increased from 1,300 to 2,600. All visit predictions were at the higher level of CAMPS adjusted by the same calibration factor as above (6.72). The benefit of the additional camp sites is the area between the two demand curves. The number of 1991 visitors predicted with 2,600 camp sites is about 1,054,000, an increase of about 148,000 visits.

At a per-visit benefit of $9.51 in 1991 dollars, the total benefit of the additional camp sites is about $1.4 million. The annual benefit per camp site added is about $1,100 in 1991 dollars, or $1,170 in 1994 dollars. Note that the value of $1,170 is similar to the marginal value of the fist added camp sites at Table Rock Lake given in Table 25d ($1,260). The slight difference occurs because the 1,300th added camp site produces less benefit than the fist added site.

Charging a $2 Day-Use Fee at J. Percy Priest Lake

The procedure for plotting day-use demand curves for J. Percy Priest Lake is similar to the steps described previously. Since the day-use fee is assumed to affect only day users, camping demand remains constant. Since only the day-use market area needs to be considered, only those counties within the day-use market area of 125 miles should be considered. For J. Percy Priest Lake, this amounts to 76 counties. Where possible, demographic and site-level data were updated for these observations to 1991 values. The Nashville day-use model presented in Table 13, main text, was run using the updated data set. An unadjusted prediction of 795,000 was obtained. Actual 1991 day-use visitation was estimated to be 7,796,000. The adjustment factor to correctly predict visitation is calculated as 7,796,000/795,000 = 9.81. This produces the point along X-axis for the base demand curve in Figure E2.

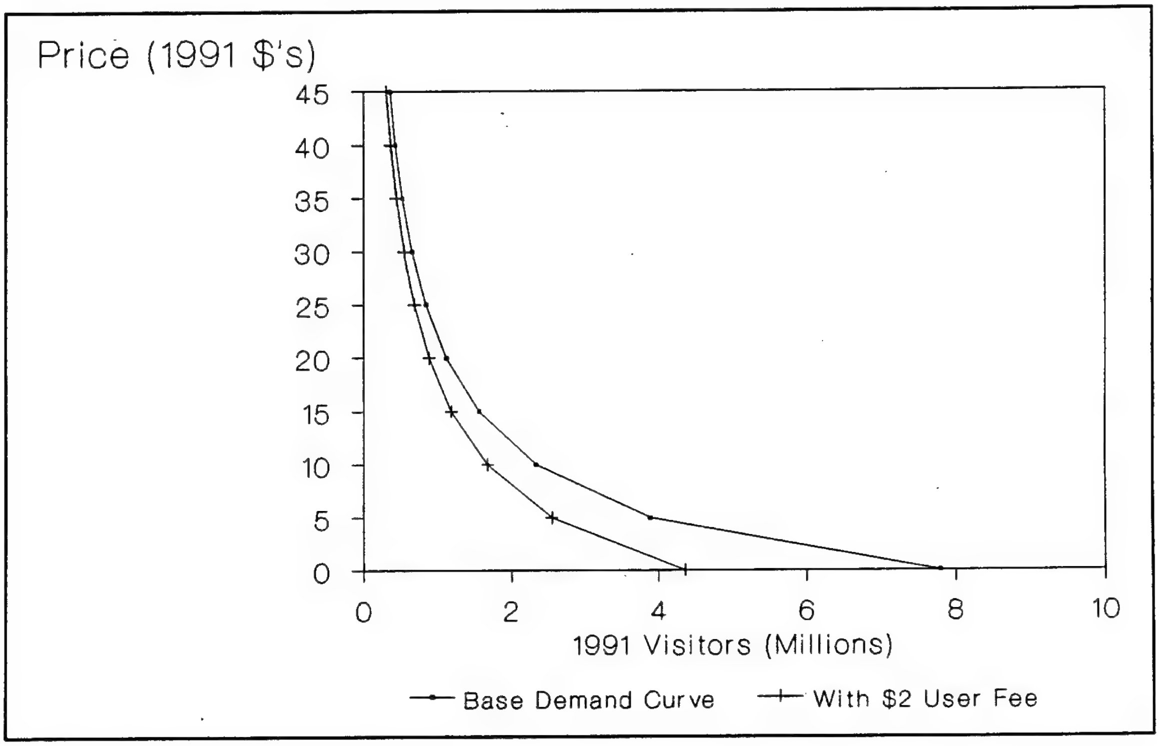

Figure E2. Day-use demand, J. Perry Priest Lake

The rest of the demand curve is obtained by increasing the price of a day-use visit. Note that the maximum observed travel cost for day-use visitors in the Nashville District is given in Chapter 4 to be $27.14 in 1980 dollars, or $44.90 in 1991 dollars. The demand curve in Figure E2 is drawn up to this limit.

The average benefit per day-use visitor for J. Percy Priest Lake is given as $5.40 (about $4.95 in 1991 dollars). The total benefit for day users in 1991

is thus nearly $39 million in 1991 dollars. The area under the base demand curve in Figure E2 corresponds to this benefit value.

The second (left) demand curve in Figure E2 considers the impact of $2.00 per vehicle day-use fee in 1991. The fee must be converted to a per-visitor basis in 1980 dollars. Table 27a indicates that the average vehicle entering J. Percy Priest Lake contains 2.02 visitors. A $2.00 per-vehicle charge equates to a $2.00/2.02 = $0.99 fee per person. In 1980 dollars, this reduces to a $0.99/0.605 = $0.60 fee increase. Note that Figure E2 shows nearly a 50-percent decrease in visitation as a result of the fee. Base visitation with the $2.00 entrance fee is estimated by the model to be about 4.4 million. The loss in consumer surplus is the area between the two demand curves. The area represents a consumer surplus loss of about $22 million in 1991 dollars. However, about $9 million in entrance fees would be collected to offset some of the consumer surplus loss.

Effects of Low Water Levels at Lake Mendocino

The final graphical application is somewhat more complicated since low water levels affect both day users and campers. The final demand curves include an aggregate of both day users and campers. The data set for Lake Mendocino includes 23 counties for the camping market area of 175 miles and 14 counties in the 125 mile day-use market area. These datasets were updated to 1991 values where possible. Actual day-use visitation at Lake Mendocino in 1991 was estimated as 1,098,000 and camping visitation as 209,000. The value of PCT_FULL at Lake Mendocino for 1991 was calculated to be 100.

Figure E3 shows how the day-use and camping demand curves are aggregated to obtain a total demand curve for a site. First, the model is run using the separate day-use and camping data sets. The unadjusted visit predictions are 89,700 for the camping model and 2,527,000 for the day-use model. The calibration factor for the day-use model is 1,098,000/2,527,000 = 0.435 and for the camping model, it is 209,000/89,700 = 2.330. A separate day-use and camping demand curve is constructed in Figure E3 using the same methods as described above. The aggregate demand curve is the sum of the day-use and camping visitor totals at each price. For example, at a price increase of $5, the models predict about 260,000 day-users and 150,000 campers. The aggregate demand in Figure E3 for a $5 price increase is the sum of the two predictions, 410,000 visitors. Note that the day-use demand curve is only drawn up to the maximum observed day-use travel cost. Chapter 4 lists the maximum day-use travel cost as $25.92 for the Sacramento District (about $43 in 1991 dollars) and the maximum camping travel cost as $38.60 (about $64 in 1991 dollars). The day-use demand curve ends before the top of the graph to avoid extrapolation of the predictions beyond the scope of the day-use model.

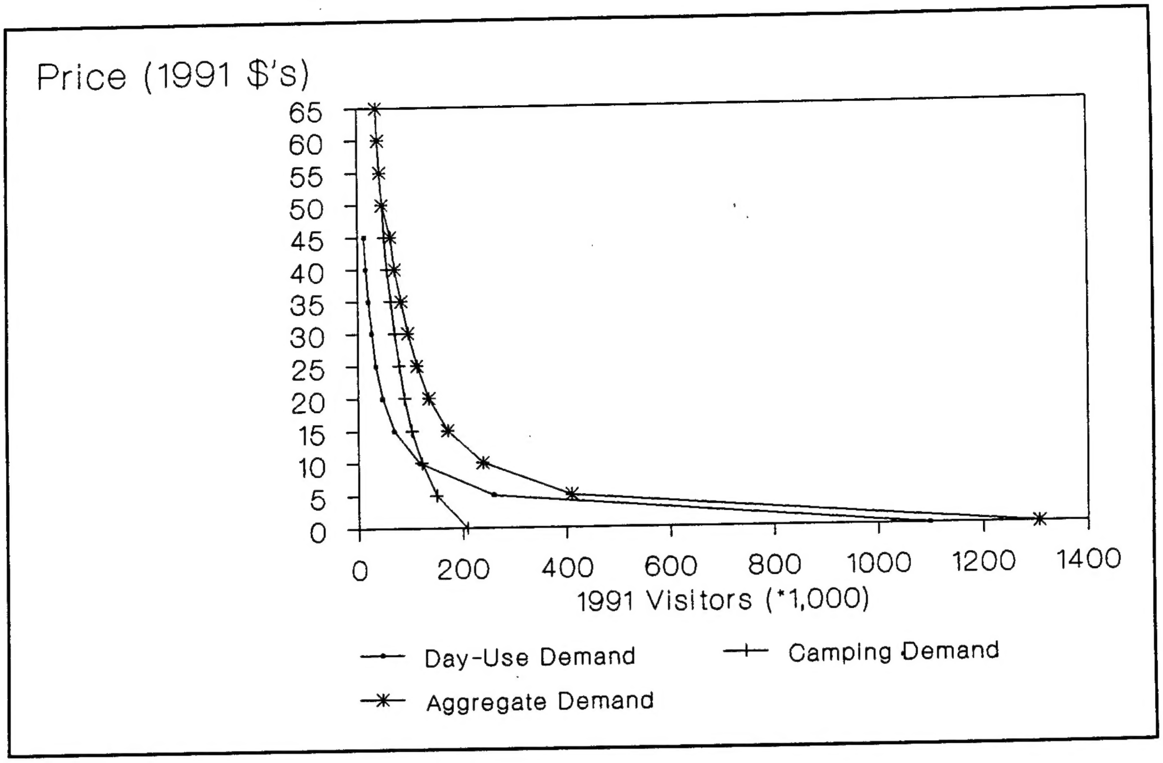

Figure E3. Lake Mendocino aggregate demand

Figure E4 illustrates the effect of reducing water levels at Lake Mendocino. The demand curves are an aggregate of day users and campers. The base demand curve in Figure E4 is the same as the aggregate demand curve in Figure E3. The management change considered in Figure E4 is a change of PCT_FULL from 100 to 70. Because Lake Mendocino is 1,785 surface acres at the recreation pool, changing PCT_FULL to 70 is associated with a surface area of 1,250 acres. Lake levels at Lake Mendocino did actually reach this level in the fall of 1987. As described in Chapter 5, consequences of more complicated water management schemes, such as holding additional water during a certain month, can be analyzed using the models.

Figure E4 shows that overall visitation is predicted to decrease by about 30 percent as a result of the low water levels. Camping visitation drops from 209,000 to 142,000, a loss of 67,000 visitors. Table 22 lists the average per-user camping benefit as $10.84 ($9.93 in 1991 dollars). The consumer surplus loss from the low water to campers is estimated to be $9.93 * 67,000 = $665,000 in 1991 dollars. Day-use visitation is predicted to drop from 1,098,000 to 745,000. The average per-user day-use benefit is given as $1.87 in Table 22 ($1.72 in 1991 dollars). The consumer surplus loss to day users would be $1.72 * 353,000 = $607,000. The aggregate consumer surplus loss is about $1.3 million in 1991 dollars.

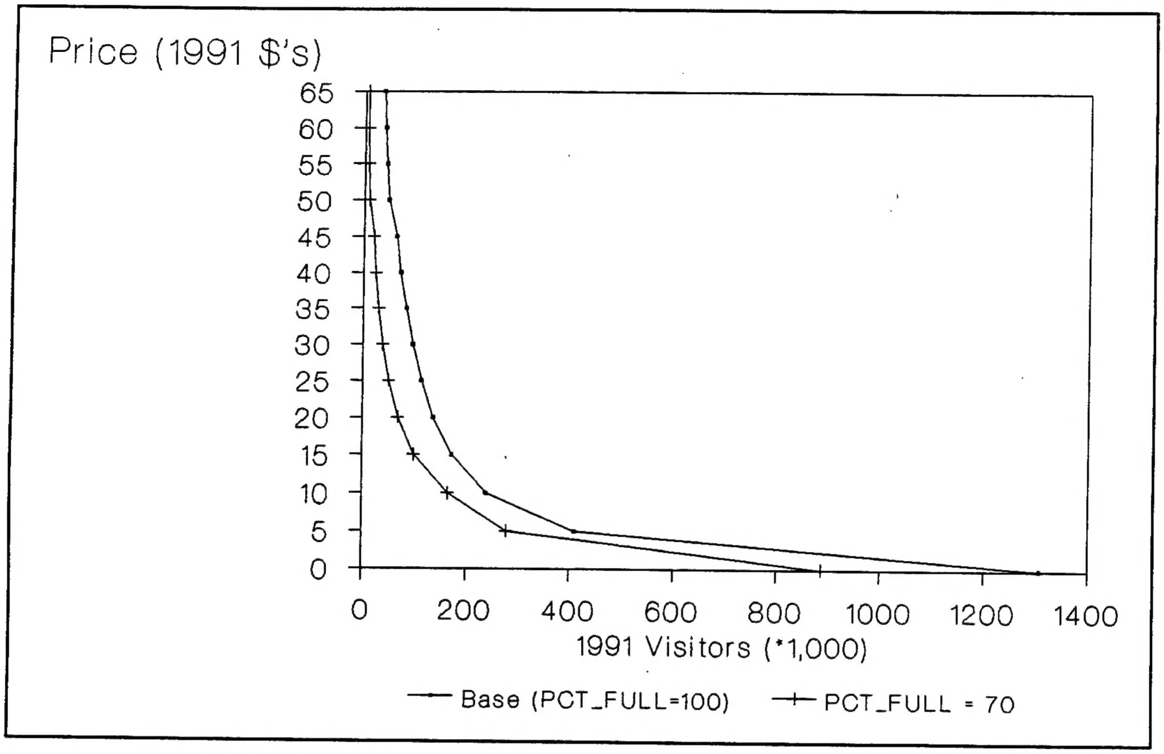

Figure A4. Impact of low water, Lake Mendocino

Conclusion

The graphs presented in this section illustrate the economic theory used to assess consequences of various management actions. An application similar to those presented in this section can be accomplished within a day, once one becomes familiar with the models. Applications which consider sites which were not included in the analysis will take longer since the base data must be constructed. Using the pooled models presented in Table 15 allow applications using any U.S. Army Corps of Engineers project.

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13. ABSTRACT *(Maximum 200 words)*

This report documents the development and application of regional recreation demand models (RRDM) developed for U.S. Army Corps of Engineers (Corps) multipurpose reservoirs. RRDMs are used to estimate the contribution of recreation resources to national economic development (NED) benefits. NED benefits from recreation are the consumer surplus estimated from the RRDM travel cost models. The report describes development of the database, estimation of the regional models using visitation, and reservoir and market area data for projects in the Corps' Nashville, Little Rock, and Sacramento districts. Using regression analysis, visitation rates vary with travel costs per visit, population from counties of origin, reservoir facilities, substitute water-based recreation opportunities, and demographic factors. Applications of the developed models estimated the per-visitor benefits at the reservoirs; economic benefits from holding water in storage for recreation and reservoir fluctuation; economic benefits from constructing additional recreation facilities; impact on visitation and benefits from charging or increasing fees; and impact of changing market area demographics (recreation use by ethnic and aging populations). Application or transfer of models estimated in one region to reservoirs in other regions (not included in RRDM development) showed robust results for transfer of average benefits and transfer of incremental values of added facilities. Transfer of predicted visitation estimates was adequate when conditions at the study and target reservoirs were similar.

14. SUBJECT TERMS
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